Doctoral Dissertation

Mitigating Social Desirability Bias: Application of List Experiment in Education and Agriculture Sectors

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We hereby recommend that the dissertation by Mr. NGUYEN MANH HUNG entitled "Mitigating Social Desirability Bias: Application of List Experiment in Education and Agriculture Sectors" be accepted in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY IN ECONOMICS.

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Abstract

This dissertation investigates the utility of list experiments as a methodological tool in social sciences, focusing on its advancement to elicit truthful responses on sensitive topics while mitigating social desirability bias. Through a comprehensive literature review and the implementation of multiple list experiments, this research demonstrates the efficacy of indirect questioning techniques in exploring sensitive issues within the domains of education and agriculture.

This dissertation has three research objectives: (i) Exploring heterogeneous effects among sub-samples from list experiment's outcomes, (ii) Utilizing list experiment in the education sector, and (iii) Utilizing list experiment in the the agriculture sector. These objectives are pursued across three core chapters (chapter 2, chapter 3, and chapter 4), each presenting empirical data and policy implications derived from list experiment findings. The first research objective is addressed in all core chapters.

Next, Chapter 2 addresses the second research objective by uncovering academic cheating behaviors among 1,386 Vietnamese undergraduates. Using list experiments, the study reveals a significant discrepancy between reported academic cheating prevalence obtained via indirect questioning versus direct questioning methods. Furthermore, female students exhibit higher incidences of academic cheating in later academic years, while male students engage in cheating across all grades. This chapter highlights the heterogeneous effects of academic cheating by gender and grade.

Chapter 3 focuses on the third research objective, exploring issues of pesticide practice noncompliance and trust in extension services among 876 green tea farmers in Vietnam. The findings indicate substantial underreporting of noncompliance with pesticide practice regulations when using direct questioning methods, compared to the higher prevalence revealed through list experiments. This chapter highlights the disparity in pesticide practice noncompliance by gender.

Chapter 4 also aims to obtain the third objective by extending the analysis of farmers' trust in extension services, using cross-randomization techniques within the

same sample of Chapter 3. The results reveal the overeport of trust levels obtained via direct questioning method, highlighting the efficacy of list experiments in minimizing biases related to social desirability and political apprehension. Specifically, there are age-related variations in perceptions of credibility and influence among extension services.

The implications of the findings are discussed in the final chapter. Policy recommendations emphasize the need for tailored interventions that account for gender and age disparities in educational and agricultural contexts. Addressing these disparities can enhance equity and effectiveness in policy-making, ensuring fair access to resources and opportunities across diverse demographic groups. Moreover, the dissertation advocates for the broader adoption of indirect questioning techniques in sensitive topic research, emphasizing their role in producing more reliable data compared to traditional survey methods.

In conclusion, this dissertation contributes to advancing methodological practices in social science research by demonstrating the utility of list experiments in uncovering hidden behaviors and perceptions. By addressing gaps in understanding and offering practical insights for policy and practice, this dissertation underscores the transformative potential of indirect questioning techniques in investigating complex societal issues with sensitivity.

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This dissertation is dedicated to all those who have supported me, directly or indirectly, along this path.

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Abbreviations

AI	**A**rtificial **I**ntelligence
GLOBAL GAP	**Global G**ood **A**gricultural **P**ractice
LEOs	**L**ocal **E**xtension **O**fficers
PHI	**P**re-**H**arvest **I**nterval
VHs	**V**illage **H**ead**s**
VietGAP	**Viet**nam **G**ood **A**gricultural **P**ractice

Chapter 1. Introduction

1.1. List experiment

1.1.1. Basic design

The list experiment, also referred to as the item count technique or unmatched count technique, is a survey method used in social sciences and polling to collect sensitive or confidential information from respondents while maintaining their anonymity (Blair & Imai, 2012; Li & Van den Noortgate 2022; Igarashi & Nagayoshi, 2022). List experiment focused on minimizing social desirability bias, a common issue where respondents provide answers they believe are more socially acceptable rather than reflecting their true beliefs or behaviors. List experiments emerged as a promising alternative by embedding sensitive items within a longer list of nonsensitive items, thus reducing the risk of disclosure and enhancing respondent privacy. The indirect questioning method is especially effective for examining sensitive topics that respondents may be reluctant to admit openly, such as illegal activities, socially undesirable behaviors, or stigmatized beliefs (Hinsley et al., 2019).

Regarding social desirability bias, this phenomenon occurs when respondents tend to provide answers that they believe are socially acceptable or desirable, rather than accurately reflecting their true beliefs, attitudes, or behaviors (Blair & Imai, 2012). Social desirability bias can affect various aspects of research, including surveys, interviews, and self-report measures. Importantly, social desirability bias can distort research findings by presenting a skewed picture of reality. Since participants do not provide truthful responses, the data collected potentially reflects the fake prevalence or nature of behaviors, attitudes, or opinions being investigated.

List experiments offer valuable advantages over traditional survey techniques based on direct questioning. First, this indirect questioning method allows for gathering data on sensitive topics without directly asking respondents to disclose potentially stigmatizing information, thereby reducing social desirability bias. This indirect approach helps to capture more accurate and honest responses, especially on issues like drug use, discrimination, or political preferences.

Second, list experiments protect respondent anonymity and confidentiality, which is crucial in studies involving vulnerable populations or topics where privacy concerns are paramount. By embedding sensitive items within a larger list, researchers can create a plausible deniability framework that encourages truthful reporting while maintaining respondent trust.

The basic design of the list experiment includes two distinct groups: the control group and the treatment group. The control group is presented with a list containing n nonsensitive statements. The treatment group contains the same n nonsensitive statements as the control group, plus an additional sensitive statement. Respondents are then required to report only the total number of statements that are associated with them without specifying exactly specific statements (Blair & Imai, 2012). The prevalence of sensitive behavior is measured by comparing the average number of statements reported between the control group and the treatment group. The difference in averages is used to infer the prevalence of the sensitive item without revealing individual responses - an indirect questioning approach. The key assumption in the list experiment is that respondents in both groups will, on average, provide truthful answers about nonsensitive statements (Imai, 2011). Therefore, any difference in the average counts between the treatment and groups can be attributed to the prevalence of respondents who are associated with the sensitive statements.

1.1.2. Application of list experiment in social sciences

Previous studies illustrate the efficacy of the list experiment in diverse contexts. For instance, Lépine et al. (2020) applied a double-list experiment to assess unprotected sex among female sex workers in Senegal and intimate partner violence (IPV) among women in rural Burkina Faso. Their findings indicated a significant reduction in misreporting, with the prevalence of sensitive behaviors reported more accurately compared to direct questioning methods. Specifically, the list experiment reduced misreporting by 17 percentage points for condom use and by 16–20 percentage points for IPV, demonstrating its robustness in improving the accuracy of sensitive health behavior data in low-literacy and high-poverty settings.

In terms of the political field, Eriksen et al. (2018) focused on measuring actual support for sensitive political issues, showcasing the method's ability to uncover genuine public opinions that might otherwise be masked by social desirability bias. Song et al. (2022) investigate the phenomenon of vote-buying among Mexican immigrants residing in the United States. The findings reveal that vote-buying is indeed a significant issue among this population, with a notable portion of respondents indicating that they had been targeted by vote-buying efforts. The results also suggest that these efforts are not random but are systematically directed at certain segments of the immigrant population, particularly those with stronger ties to their home country and a higher propensity to participate in Mexican elections. Other scholars such as Nicholson and Huang (2022) delve into the complexities of measuring political trust in China, a context where social desirability bias is particularly pronounced. This study critically examines how social desirability influences responses to survey questions about political trust, challenging existing assumptions and methodologies. The findings reveal that political trust in China may be significantly lower than previously reported. Their results suggest that when the social desirability bias is accounted for, a substantial portion of the population exhibits skepticism towards the government. These outcomes contradict the high levels of reported trust typically observed in direct surveys.

Regarding the attitude disparity by gender, Asadullah et al., (2021) employ list experiments to measure gender attitudes across diverse populations, focusing on areas where gender norms are deeply entrenched and traditional survey methods often fail to elicit honest responses. The study's findings reveal significant discrepancies between responses obtained through direct questioning and those obtained via list experiments. The latter method uncovers a higher prevalence of traditional gender attitudes than what is typically reported in conventional surveys. This study suggests that social desirability bias substantially influences the reporting of gender attitudes, leading to an underestimation of traditional or discriminatory views.

In terms of immigrant issues, Igarashi and Nagayoshi (2022) delve into the intricate dynamics of prejudice and societal norms concerning attitudes towards immigrants in Japan. Employing list experiments, they investigate the nuanced manifestations of prejudice within Japanese society. By employing a methodology that allows respondents to disclose sensitive attitudes anonymously, the study offers insights into the prevalence and underlying factors influencing prejudiced attitudes towards immigrants. Through rigorous analysis of survey data, this study uncovers the complex interplay between individual attitudes and social norms, shedding light on the mechanisms through which prejudice is both perpetuated and challenged within Japanese society. The findings contribute not only to the understanding of attitudes towards immigrants in Japan but also to broader discussions on the dynamics of prejudice and social norms in diverse cultural contexts. Other scholars such as Harris et al., (2018) undertake a comprehensive analysis of the economic determinants underlying anti-immigrant prejudice in South Africa. By interrogating the interplay between economic conditions, political factors, and social dynamics, the authors provide valuable insights into the drivers of anti-immigrant prejudice in a diverse and dynamic society.

With regard to food insecurity issue, Tadesse et al. (2020) employ a list experiment approach to investigate biases inherent in self-reported measures of food insecurity. This study offers insights into the complex dynamics underlying individuals' willingness to disclose food insecurity experiences, highlighting the importance of accounting for such biases in research and policy efforts aimed at addressing food insecurity. The findings contribute to advancing methodological practices in food security research and provide valuable implications for the design and implementation of interventions to alleviate food insecurity worldwide.

While list experiments offer an effective approach for addressing sensitive topics in social science research, there are remaining fields where further exploration and development are needed to enhance knowledge. The next subsection will provide research gaps among current literature which employed list experiment.

1.2. Research gaps

Although previous studies have provided valuable insights by applying list experiment in a wide range of sectors in social sciences, noticeable research gaps remain as follows:

(i) **Research Gap 1**: Heterogeneity in treatment effects among subsamples in the list experiment's outcomes receives less attention from previous scholars.

(ii) **Research Gap 2**: Sensitive issues in the education sector remain understudied.

(iii) **Research Gap 3**: Sensitive issues in the agriculture sector remain understudied.

First, investigating heterogeneous effects among subsamples in research is essential for providing nuanced insights into complex phenomena, guiding policy decisions, and promoting equity and fairness. Different groups within a population may respond to interventions, policies, or phenomena in varying ways. By examining heterogeneous effects, researchers can uncover nuances in how these relationships manifest across diverse subgroups. This precision allows for tailored interventions or policies that address specific needs or challenges faced by different segments of the population. Furthermore, heterogeneous effects analysis helps identify moderating factors that influence the strength or direction of relationships between variables. These factors could be demographic characteristics (e.g., age, gender, socio-economic status), contextual factors (e.g., geographic location, institutional settings), or psychological factors (e.g., attitudes, beliefs). Understanding these moderators provides insights into why and under what conditions certain outcomes occur, offering opportunities for targeted interventions or personalized approaches. Importantly, failure to investigate heterogeneous effects may lead to over-generalization of findings across the entire population. By examining heterogeneity, researchers can avoid making sweeping conclusions that may not hold universally, thereby enhancing the validity and reliability of their research.

Second, there are a lot of sensitive issues that remain understudied in the education sector. For instance, academic cheating raises concern among previous scholars such as Ossai et al., (2023), Park (2020), and Ababneh et al. (2022). Though their findings provide valuable insights to deepen understanding of academic cheating, the accuracy of outcomes remains doubtful since most studies employ direct questioning methods to investigate the situation of academic cheating. As a result, the result might be biased due to social desirability bias.

Third, many sensitive issues in the agriculture sector have received inadequate attention from previous researchers. In terms of pesticide application, previous studies such as Möhring et al. (2020), Sun et al. (2019), and Schreinemachers et al. (2020) delve into examining the practice behavior of pesticide users. Other studies utilize surveys or questionnaires based on basic direct questioning to investigate the credibility of agricultural extension sources among farmers such as Madaki et al., (2023) and Jallow et al. (2017). However, social desirability bias might potentially affect the validity of outcomes since pesticide practice behaviors and the credibility of extension sources retain a high level of sensitivity among farmers.

1.3. Research objectives

This subsection provides the research objective of the dissertation. Based on the three above-mentioned research gaps, this dissertation has three research objectives as follows:

(i) **Research Objective 1**: Examining heterogeneous effects among sub-samples from list experiment's outcomes (Chapter 2, Chapter 3, and Chapter 4).

(ii) **Research Objective 2**: Utilizing list experiment in the education sector (Chapter 2).

(iii) **Research Objective 3**: Utilizing list experiment in the agriculture sector (Chapter 3 and Chapter 4)

1.4. Dissertation structure

To attain the three mentioned research objectives, this dissertation includes 5 chapters with the structure presented in Figure 1.1. Chapter 1 provided background information of the list experiment and why the list experiment is essential to investigate sensitive issues in the education and agriculture sectors. Chapters 2, chapter 3, and chapter 4 are the main contents of the dissertation, which provide data and outcomes to obtain the three research objectives. Further analysis of heterogeneity in treatment effects among subsamples is carried out in all three core chapters to obtain the first research objective.

Next, chapter 2 attains the second research objective by using the list experiment to unmask academic cheating behavior in the artificial intelligence era. This chapter investigates whether students conceal truthful responses to AI-powered academic cheating behaviors by utilizing a sample of 1,386 Vietnamese undergraduates. Based on the outcomes of the list experiment, policy implications are suggested to safeguard academic integrity.

Chapter 3 aims to obtain the third research objective. This chapter investigates the sensitive issues related to pesticide practice in the agriculture sector. By unveiling noncompliance with pesticide practice disciplines among 786 Vietnamese green tea farmers, this chapter reveals concealment in response to pesticide practice among producers and further implications to promote sustainable agriculture.

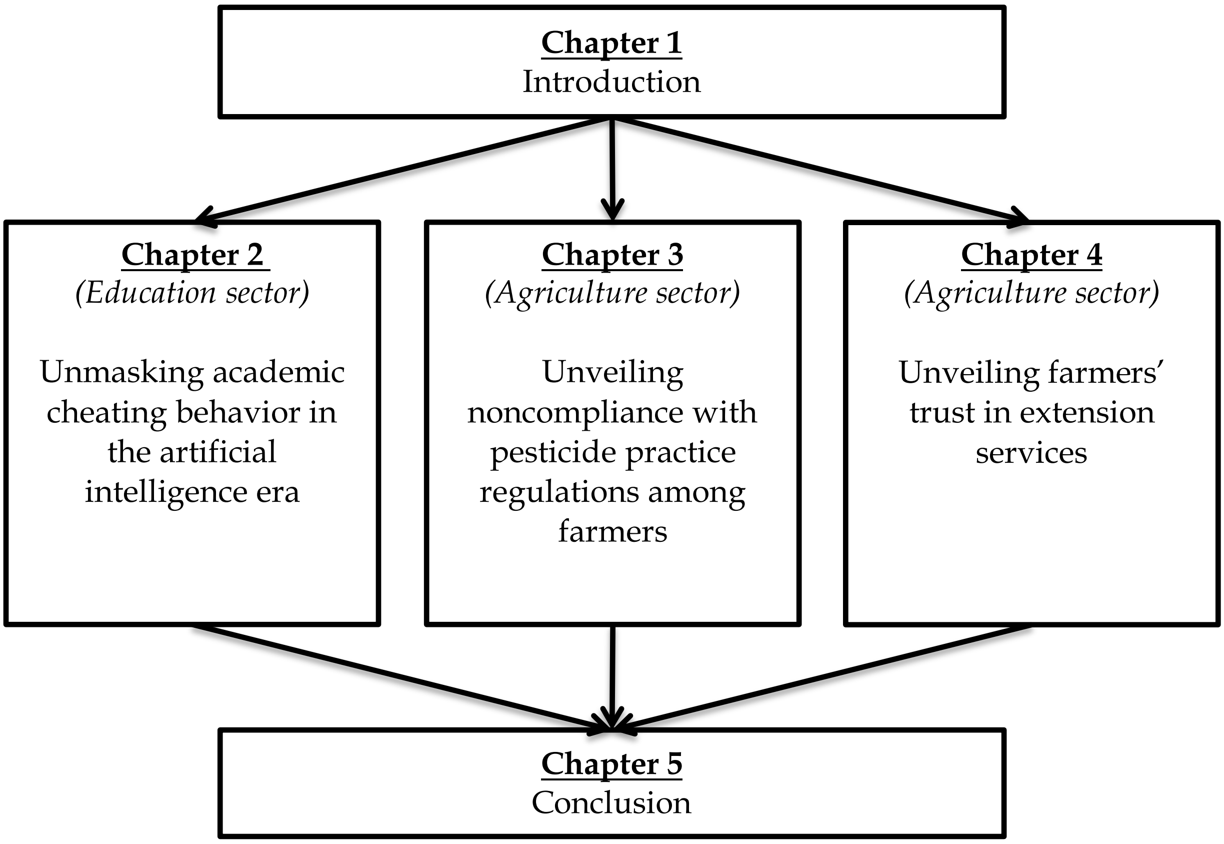

Figure 1.1. Structure of dissertation

Chapter 4 aims to attain the third research objective. Applying cross-randomization with the same sample as Chapter 3, this chapter examines farmers' trust in local extension services among agricultural producers. List experiment is employed to minimize social desirability bias caused by local relationships and political fear. In addition, policy implications are recommended to promote effective agricultural extension among local communities.

Chapter 5 summarizes the findings from the three core chapters. Based on the findings, this chapter presents conclusions and discusses essential policy implications. In addition, chapter 5 acknowledges the limitations of this dissertation and further provides suggestions for future research.

Chapter 2. Unmasking academic cheating behavior in the artificial intelligence era

2.1. Introduction

Artificial intelligence (AI) has emerged as a transformative technology, reshaping how businesses and individuals interact, communicate, and access services (Kutyauripo et al., 2023; Phan et al., 2023; Olan et al., 2022; Wang et al., 2023). The rapid adoption of these intelligent virtual applications has occurred across many sectors such as business, agriculture, transportation, and healthcare services (Ali et al., 2023; Du et al., 2023; Kulkov, 2021; Kumar et al., 2023; Wang et al., 2022). In a similar vein, the field of education has undergone significant transformation with the incorporation of AI applications (Mubin et al., 2020; Qu et al., 2022; Udupa, 2022). Specifically, AI virtual assistants are altering teacher-student interactions, content delivery, and learning methods (Aung et al., 2022; Dai et al., 2023). By providing detailed instruction, instantaneous assistance, greater interactivity, and streamlined administration, AI-powered chatbots are revolutionizing the educational system (Ratten & Jones, 2023). Education is improved in terms of accessibility, efficiency, and engagement through the use of AI virtual assistants. AI-powered chatbots transform lectures to become more accessible and productive for all educational stakeholders (Kasneci et al., 2023).

While AI-powered applications offer many valuable outcomes in the field of education, there are also a lot of potential drawbacks regarding data privacy, accuracy, overreliance, and ethical concerns (Guo et al., 2023; Kasneci et al., 2023; Koo, 2023; Sollosy & McInerney, 2022). Importantly, academic misconduct issues have been raised by the intervention of AI-powered chatbots, which present challenging problems for educational institutions (Fyfe, 2023; Sweeney, 2023). AI-powered chatbots, which are outfitted with sophisticated algorithms and capabilities, provide students with a wide range of assistance during assignments or exams (Ansari et al., 2023; Cotton et al., 2023; Currie, 2023; Dalalah & Dalalah, 2023; Moisset & Ciampi De Andrade, 2023). With the assistance of AI chatbots, students can quickly and easily access auto-generated answers, responses, or plagiarized content, pushing them to break the fundamental regulations of academic integrity (Bakar-Corez & Kocaman-Karoglu, 2023; Li et al., 2023). Importantly, students might intentionally use AI-generated responses for academic cheating purposes that appear highly credible but may not be easily detectable by any anti-plagiarism applications (Choi et al., 2023; Livberber & Ayvaz, 2023; Sweeney, 2023). The intricate interplay between AI chatbots and academic cheating raises emerging concerns among educational institutions in preserving the principles of academic integrity (Guo & Wang, 2023; Kasneci et al., 2023).

Although previous studies have provided valuable insights into academic cheating in the digital age, noticeable research gaps remain. First, most existing studies rely on the direct questioning approach in their data collection method to examine academic cheating behavior. For instance, Ossai et al. (2023) examined the relationship between academic performance and academic integrity among 3,214 Nigerian high school students via the direct questioning approach in the paper survey[1]. Similarly, Park (2020) examined a sample of 2,360 Korean college students by employing direct questions to measure the frequency of cheating behaviors with a 5-point Likert scale[2]. Regarding the differences in academic cheating behavior in online education and face-to-face education, Ababneh et al. (2022) used online questionnaires to investigate 176 UAE undergraduates[3]. However, examining highly sensitive issues such as academic cheating by direct questioning approach may raise concerns about the reliability of outcomes due to the effect of social desirability bias. Specifically, social desirability bias is a widely observed phenomenon wherein individuals provide untruthful responses to align with societal norms or expectations, thus positively presenting themselves, rather than revealing accurate or precise information (Blair & Imai, 2012). Biased responses can arise from the predilection to pursue social validation or the repulsion towards criticism. Importantly, social desirability bias potentially manifests in diverse settings, encompassing interviews, surveys, or other data collection methods that focus on

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[1] Ossai et al. (2023) used the following direct statement to measure cheating behavior: *"I sometimes copy already prepared assignments from my friends"*.

[2] Park (2020) used the following direct question to measure cheating behavior: *"How often did you conduct the following behaviors in the past semester?"*.

[3] Ababneh et al. (2022) used the following direct question to measure cheating behavior: *"During the past year, how frequently did you cheat on online tests/exams at your university"*.

self-reporting, notwithstanding the anonymity afforded by these approaches (Larson, 2019). As a result, social desirability bias can significantly compromise the credibility and accuracy of research outcomes. The skewing of data resulting from untruthful participants can bias the findings and produce erroneous conclusions (Ahmad et al., 2023; Latkin et al., 2017; Ried et al., 2022). In the context of the education sector, direct responses to academic cheating might be biased, as students might conceal academic cheating behavior for a variety of reasons, often rooted in a complex interplay of academic and social reasons. Regarding academic reasons, cheating is typically considered a violation of academic integrity regulations and can result in disciplinary actions, ranging from failing a specific assignment to even expulsion from the institution. In terms of social reasons, admitting to academic dishonesty might harm student's self-esteem and reputation. As such, students may conceal their cheating behavior in basic direct questioning to avoid unexpected consequences.

Second, numerous studies have extensively examined the heterogeneity in cheating behavior by gender. For instance, Yazici et al. (2023) indicate that females report a lower prevalence of academic cheating in face-to-face education. In a similar vein, Mohd Salleh et al. (2013) highlighted that male students are more likely to violate academic integrity than their counterparts. Conversely, Ezquerra et al. (2018) and Ip et al. (2018) revealed that no difference in academic cheating exists between males and females. In addition to valuable findings related to heterogeneity in academic cheating behavior by gender, the disparity in academic cheating behavior by gender across different grades remains understudied.

Addressing these gaps is essential for developing a comprehensive understanding of academic cheating in the era of AI. This study aims to answer the two following research questions:

(i) Do students under-report AI-powered academic cheating behaviors in direct questioning?

(ii) Does farmers' noncompliance with pesticide practice regulations differ by gender?

Regarding the scope of cheating behaviors in our study, we focus on cheating history (students who had cheated) and cheating intention (students who intend to cheat in the future). By delving into this question, our study aims to uncover not only the current situation of AI-powered academic cheating among undergraduates but also the heterogeneity of AI-powered academic cheating observed among students from diverse individual characteristics. To do so, we examine a sample of 1,386 Vietnamese undergraduates to unveil academic cheating behaviors by using ChatGPT (Generative Pretrained Transformer), which is an AI-powered language model developed by OpenAI. In terms of popularity, ChatGPT reached 100 million monthly active users just two months after its launch in November 2022 and became the fastest-growing consumer application in history (UBS, 2023). Based on the reliable outcomes of the list experiment, our study contributes valuable insights that inform policy formulation and management strategies, ultimately striving for academic integrity in the Fourth Industrial Revolution.

The remainder of this chapter is structured as follows: Section 2.2 provides data descriptions. Section 2.3 describes the research methodology and the experiment design to investigate academic cheating behaviors among undergraduates. Section 2.4 presents the main findings. Section 2.5 provides discussions based on empirical findings. The last section provides conclusions and explores the potential implications of preventing AI-powered academic cheating.

2.2. Data collection

Our study was conducted in May 2023. We focused on one of three Vietnam regional universities, Thai Nguyen University. The experiment included three stages. In the first stage, we sent the collaboration invitations to all 9 graduate schools of Thai Nguyen University, as these administrative formalities are mandatory in Vietnam. Consequently, we obtained acceptance letters from 4 graduate schools as follows: Graduate School of Education, Graduate School of Medicine and Pharmacy, Graduate School of Engineering, and Graduate School of Information Technology. We then confirmed the total number of undergraduates in all participating graduate schools and selected an initial sample of 1,450 participants. The number of participants in each graduate school was proportionally limited to the total number of undergraduates in all four schools. In the second stage, we transferred survey invitations attached with QR code access to the online survey powered by Qualtrics to participating graduate schools. In the last stage, each graduate school distributed survey invitations to all their undergraduates via internal management systems. The number of responses in each graduate school was proportionally limited by the system according to the total number of students in all 4 graduate schools. From 9 May 2023 to 12 May 2023, we received a total of 1,386 valid responses. The distribution of respondents across the four universities is shown in Table A.1.

Regarding the awareness among undergraduates about punishment for academic misconduct, all participating graduate schools regularly inform their students about the punishment policy for academic cheating (including AI-powered academic cheating) at the beginning of each academic semester. All academic misconduct is highly prohibited and offenders have to face strict punishments including expulsion from educational institutions[4].

Table 2.1. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Age *(years)*	20.307	1.367	18	29
Gender *(1=male, 0= female)*	0.573	0.495	0	1
Grade *(1=Higher-grade student, 0=newly enrolled student)*	0.361	0.481	0	1
Ethnicity *(1=minority, 0=majority)*	0.266	0.442	0	1
Social association *(1=member, 0=nonmember)*	0.712	0.453	0	1
Part-time job *(1=yes, 0=no)*	0.263	0.441	0	1

Table 2.1 shows descriptive statistics of respondents in the study. On average, students are approximately 20.3 years old. Male students are dominant, as they account for 57.3% of respondents. In terms of grade, newly enrolled students represent more than one-third of the sample[5]. Regarding ethnicity, 26.6% of

[4] As members of Thai Nguyen University, all four participating graduate schools have been applying Circular No.10/2016/TT-BGDĐT (Regulations for Student Affairs in Formal Higher Education programs) issued by the Vietnam Ministry of Education and Training to treat academic offenders. Following this circular, first-time offenders will fail the subjects in which they act academic cheating and receive a caution. For repeated offenders, punishment enhancement (expulsion from the academic institution) will be applied.

[5] We separate grades into 2 distintive groups: newly enrolled students (including freshmen and sophomores) and higher-grade students (including juniors and seniors)

respondents were minority ethnic students. In terms of after-school activities, nearly three-fourths of the students were members of social associations, while 26.3% of students reported that they engaged in part-time jobs.

2.3. Methodology

2.3.1. Experiment design

We adopt the basic design of the list experiment with a few adjustments to reveal responses to multiple academic cheating-related statements based on our sample. Specifically, we designed a control group and two separate treatment groups. Respondents were randomly allocated to one of the three groups. Table 2.2 describes the detailed experiment design. Our experiment includes two separate phases. Phase 1 (list experiment) aims to investigate AI-powered academic cheating behaviors via indirect questioning. On the other hand, Phase 2 (direct questioning) helps to investigate AI-powered academic cheating behaviors via the basic direct questioning approach.

Phase 1 has the participation of all groups. Respondents of the control group received a list containing four nonsensitive statements. Treatment group 1 received a list that includes a similar list of nonsensitive statements of the control group and an additional sensitive statement that helps to measure the prevalence of students who had cheated by using ChatGPT (cheating history). Similarly, the list for treatment group 2 is equipped with an additional sensitive statement along with four nonsensitive statements of the control group to measure the prevalence of students who intend to cheat by using ChatGPT (cheating intention). In Phase 1, all respondents are required to indicate only the total number of statements that they agree with. Consequently, we can calculate the average response value of each group. We then capture the prevalence of students who had cheated by calculating the difference in average response value between control group and treatment group 1. Similarly, the prevalence of students who intend to cheat is calculated by the difference in average response value between control group and treatment group 2.

Next, we investigated academic cheating behaviors via direct questioning (Phase 2). Only respondents in the control group participated in this phase. To guarantee the accuracy of outcomes, Phase 2 has only the participation of respondents in the control group as these respondents did not engage with sensitive statements during the list experiment, as opposed to respondents in the treatment groups. In Phase 2, respondents in the control group were required to answer only "Yes" or "No" for two direct academic cheating-related questions (cheating history and cheating intention). By doing so, we can observe the prevalence of respondents who are associated with cheating history and cheating intention via direct questioning.

2.3.2. Validation

To estimate the prevalence of sensitive behaviors, list experiments must satisfy three key assumptions: (1) random assignment, (2) no liars, and (3) no design effect (Imai, 2011). These three assumptions are empirically validated in this subsection.

First, we ran balance tests to confirm whether respondents were allocated randomly to the treatment regardless of demographic variables. Accurate causal analysis, reduced bias, increased statistical power, and generalizability all depend on list experiments having guaranteed randomization of treatment (Imai, 2011). Individuals are assigned to different treatment groups at random when randomization is used. It is crucial in any experimental design to keep the control and treatment groups similar in terms of respondent characteristics. Table 2.3 depicts the outcomes of the balance tests. Since no significant difference in respondent characteristics exists, we can confirm that random assignment was well guaranteed in our list experiment.

Second, the concept of "no liars", validated through the absence of floor and ceiling effects, plays a pivotal role within the framework of the list experiment. The floor effect manifests when certain groups of respondents consistently express disagreement with all survey statements, while the ceiling effect occurs when respondents consistently report affirmative responses to all statements. Such deceptive response patterns often stem from concerns about privacy among respondents, and these effects can undermine the reliability of estimates derived from a list experiment. If a significant number of respondents consistently select extreme response options, the accuracy of the estimated prevalence of sensitive attitudes is questioned (Blair & Imai, 2012). To counteract these effects, we applied the design method of Glynn (2013) by including at least one nonsensitive statement predicted to be rejected by the majority of respondents and another nonsensitive statement predicted to be accepted by the majority. Based on the distribution of response values presented in Table A.2, it is evident that there were no instances of ceiling or floor effects, as the proportions of entirely affirmative or entirely negative responses in our list experiment were all below 9% of all responses.

Table 2.2. Experiment design of Chapter 2

<table>
<tr><th rowspan="2">Procedure</th><th colspan="3">Group</th></tr>
<tr><th>Control group</th><th>Treatment group 1</th><th>Treatment group 2</th></tr>
<tr><td>Phase 1
(List experiment)</td><td>Please indicate HOW MANY statements you agree with.

• You had been a member of the class management board
• You had been marked highest score (A or A+) for any subjects
• You intend to attend summer courses this summer
• You intend to enroll in the master course after the undergraduate graduation</td><td>Please indicate HOW MANY statements you agree with.

• You had been a member of the class management board
• You had been marked highest score (A or A+) for any subjects
• You intend to attend summer courses this summer
• You intend to enroll in the master course after the undergraduate graduation
• You had cheated in assignments or tests by using the ChatGPT</td><td>Please indicate HOW MANY statements you agree with.

• You had been a member of the class management board
• You had been marked highest score (A or A+) for any subjects
• You intend to attend summer courses this summer
• You intend to enroll in the master course after the undergraduate graduation
• You intend to cheat in assignments or tests in the future by using the ChatGPT</td></tr>
<tr><td>Phase 2
(Direct questioning)</td><td>Please answer (YES/NO) to the following question:
• Had you cheated in assignments or tests by using the ChatGPT?
Please answer (YES/NO) to the following question:
• Do you intend to cheat in assignments or tests in the future by using ChatGPT?</td><td>Not required to participate</td><td>Not required to participate</td></tr>
</table>

Note: The order of all statements in Phase 1 and questions in Phase 2 were randomized.

Table 2.3. The balance check of Chapter 2

	C	T1	T2	T1-C	T2-C
Age *(years)*	20.243	20.370	20.307	0.128	0.064
	[1.328]	[1.473]	[1.291]	(0.092)	(0.086)
Gender *(1=male, 0= female)*	0.549	0.580	0.589	0.031	0.040
	[0.498]	[0.494]	[0.493]	(0.033)	(0.033)
Grade *(1=Higher-grade student, 0=newly enrolled student)*	0.337	0.375	0.372	0.038	0.035
	[0.473]	[0.485]	[0.484]	(0.032)	(0.032)
Ethnicity *(1=minority, 0=majority)*	0.267	0.255	0.275	-0.012	0.008
	[0.443]	[0.436]	[0.447]	(0.029)	(0.029)
Social association *(1=member, 0=nonmember)*	0.722	0.745	0.669	0.023	-0.053*
	[0.448]	[0.436]	[0.471]	(0.029)	(0.030)
Part-time job *(1=yes, 0=no)*	0.225	0.259	0.305	0.034	0.080***
	[0.418]	[0.439]	[0.461]	(0.028)	(0.029)
Observations	457	467	462	924	919

*Note: Standard deviations in square brackets. Standard errors in parenthesis.Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Finally, we examine whether the design effect appears in our list experiment. A design effect exists when the presence of a sensitive item alters respondents' tendencies to select nonsensitive items. Since list experiments rely on differences in the average value of statements chosen between treatment and control groups, the selection of nonsensitive items should not be affected by the presence of sensitive statements (Blair & Imai, 2012). Design effects pertain to alterations in an individual's responses to innocuous statements due to the inclusion of sensitive statements. They impact the dependability of results derived from a list experiment, signifying a heightened influence of intricate sampling or design elements on the estimates. Consequently, the reliability of these estimates may diminish, posing challenges for drawing precise conclusions. To address this, we applied the design effect test package of Tsai (2019) to ascertain the presence of design effects. Based on the outcomes described in Table A.3, no design effects existed in our list experiment.

2.3.3. Empirical model

Our primary objective is to examine the misreporting magnitude in responses among respondents about AI-powered academic cheating behaviors. To do so, we first estimate the prevalence of academic cheating behaviors among undergraduates via list experiment by employing the estimation model of Lépine et al., (2020), with modifications by controlling multivariates and school-level fixed effects[6] as follows:

$$Y_{is} = \alpha_1 + \tau_1 T_{is} + \mathbf{X}_{is}\delta + \theta_s + \varepsilon_{is} \qquad (1)$$

Y_{is} represents the response value (number of statements that respondent agree with) reported by respondent i in school s. α_1 is the intercept, indicating the constant term in the model. T_{is} represents binary treatment variables of respondent i in school s (T_{is} = 0 for the control group and T_{is} = 1 for the treatment group). τ_1 corresponds to the prevalence of sensitive cheating behavior, which is equivalent to the difference in average response value between the control group and treatment group. $\mathbf{X}_{is}$ is a vector of student-level covariates of respondent i in the school s, including age, gender, ethnicity, grade, social association membership, and part-time job engagement while δ is the coefficient associated with these covariates. θ_s denotes the school-level fixed effects, which capture unobserved school-specific characteristics, and ε_{is} is the error term that represents unobserved factors or random variations in the dependent variable Y_{is}.

To measure the misreporting magnitude in responses among respondents between direct questioning and indirect questioning, we consequently compare the differences in outcomes obtained via list experiment and direct questioning. To quantify this, we use the immediate form of a two-sample t-test with the unequal variances option to compare the estimated prevalence of academic cheating behaviors obtained from the list experiment with the prevalence of affirmative responses to academic cheating behavior obtained from direct questioning.

[6] To estimate the prevalence of academic cheating behaviors, the t-test for difference-in-mean estimator is qualified to compare the average response value between control group and treatment group. Howerver, we followed the model of Lépine et al., (2020) and upgraded by Ordinary Least Squares (OLS) regressions with controlling multivariates and school-level fixed effects that have advantages in statistical analysis, particularly in addressing potential biases and improving the robustness of the model.

We further examine heterogeneity in AI-powered academic cheating behaviors across different subsamples. Equation 2 represents our estimation model to evaluate the heterogeneous effects in the subsamples:

$$Y_{is} = \alpha_2 + \tau_2 T_{is} + \beta G_{is} + \gamma G_{is} \cdot T_{is} + \mathbf{X}_{is}\delta + \theta_s + v_{is} \qquad (2)$$

in which G_{is} is the subsample dummy for respondent i in school s for potential factors. For instance, when we examine the heterogeneous effects of academic cheating behaviors by gender, G_{is} is equal to 1 for male respondents and 0 for female respondents (i.e., male dummy). τ_2 indicates the prevalence of academic cheating behavior among the subsample when G_{is} = 0, which is equivalent to the difference in average response value between the control group and treatment group in that subsample. $\tau_2 + \gamma$ indicates the prevalence of sensitive cheating behavior in the subsample when G_{is} = 1. Hence, γ corresponds to the difference in the prevalence of academic cheating behavior among subsamples. v_{is} is the error term that represents unobserved factors or random variations in the dependent variable Y_{is}.

2.4. Results

Our main findings are highlighted in this section. First, we present the results of both the list experiment and direct questioning, as well as the misreporting magnitude observed from these two questioning techniques. Next, we investigate the heterogeneous effects of AI-powered academic cheating behaviors among subsamples.

2.4.1. Main results

The prevalence of students who reported that they had cheated by using ChatGPT increased significantly via the list experiment. Table 2.4 depicts the prevalence of academic cheating behaviors and the misreporting magnitude between the two questioning methods. Regarding the outcomes of direct questioning, only 9.6% of respondents reported that they had cheated. However, the prevalence of cheaters rose nearly threefold to 23.7% via the list experiment. The results suggest that confessing to cheating was an especially sensitive issue among students, as the misreporting magnitude between indirect and direct questioning was 14 percentage points (significant at the 5% level). In terms of cheating intention, no significant differences exist between the two questioning methods, as the prevalence of students reporting that they have the intention to cheat between the list experiment and the direct questioning method remains similar (21.6% and 22.5%, respectively).

Table 2.4. Main results of Chapter 2

Behavior	List experiment			Direct questioning	Misreporting magnitude (1) – (2)
	Control	Treatment	Estimated prevalence (1)	Estimated prevalence (2)	
Cheating history *(n=924)*	1.821 (0.046)	2.058 (0.051)	0.237*** (0.068)	0.096 [0.295]	0.140** (0.070)
Cheating intention *(n=919)*	1.820 (0.046)	2.036 (0.052)	0.216*** (0.069)	0.225 [0.418]	-0.009 (0.072)

*Note: Standard deviations in square brackets. Standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

2.4.2. Sub-sample analysis

Subsample analysis effectively detects differential responses or outcomes among diverse demographic, social, or contextual groups. By rigorously examining heterogeneous effects among subsamples, our study found disparities in AI-powered academic cheating behavior across different subsamples.

In terms of the heterogeneous effects of academic cheating behavior by gender, male students are more likely to use ChatGPT to cheat than female students in terms of cheating history. Figure 2.1 shows the disparity in cheating history among respondents by gender. In the pooled sample, 35.1% of male students reported that they had cheated, which is over triple the prevalence of their counterparts showing the same behavior. The magnitude of the difference between the two genders is approximately 25 percentage points, which is significant at the 10% level. Furthermore, the difference in cheating history by gender is even higher among newly enrolled students (40.1 percentage points, significant at the 5% level). Conversely, no significant differences exist in cheating history by gender in higher grades.

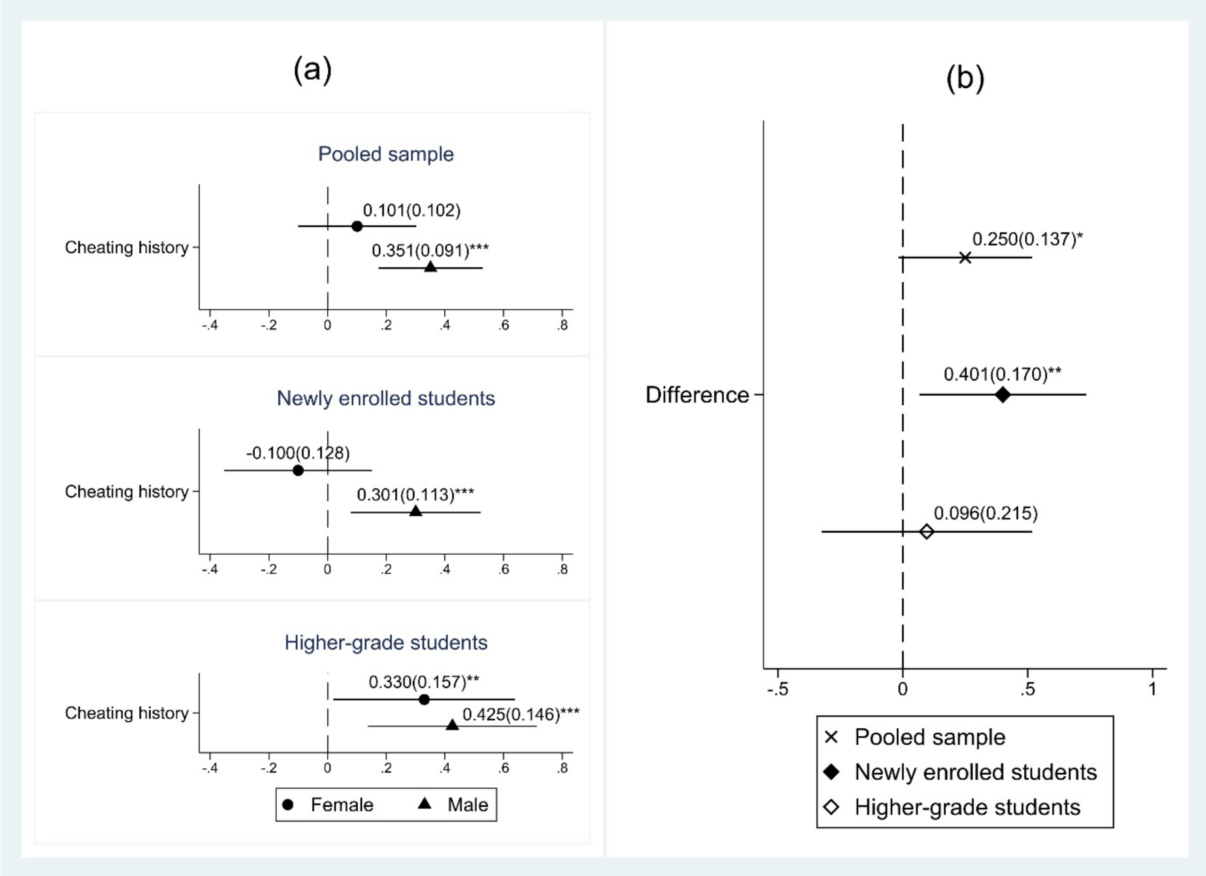

Figure 2.1. Heterogeneous effects of the cheating history by gender.

*Note: Figure 2.1a represents the estimated prevalence of respondents who reported affirmative responses to cheating history by gender. Figure 2.1b represents the disparity in cheating history by gender (male dummy). Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Importantly, the cheating history of each gender differs significantly across grades. Among female students, higher-grade female students are more likely to cheat than newly enrolled female students. As shown in Table A.4, approximately 33% of female students in higher grades reported that they had used ChatGPT to cheat, while no proof of cheating was found among newly enrolled female students. The difference in cheating history among female students across grades is 43 percentage points (significant at the 5% level). Conversely, no difference exists in cheating history among male students across grades, as male students consistently engage in academic cheating in all grades. In particular, approximately 42.5% of higher-grade male students admitted that they had cheated in comparison with 30.1% of newly enrolled male students who reported the same behavior. However, the differences in cheating history among male students across grades are not statistically significant.

With regard to the heterogeneous effects of cheating intention by gender, male and female students show no disparity in cheating intention in the pooled sample (23% and 22.4%, respectively). Correspondingly, no heterogeneous effect on academic cheating intention was found by gender across grades (as shown in Figure A.1).

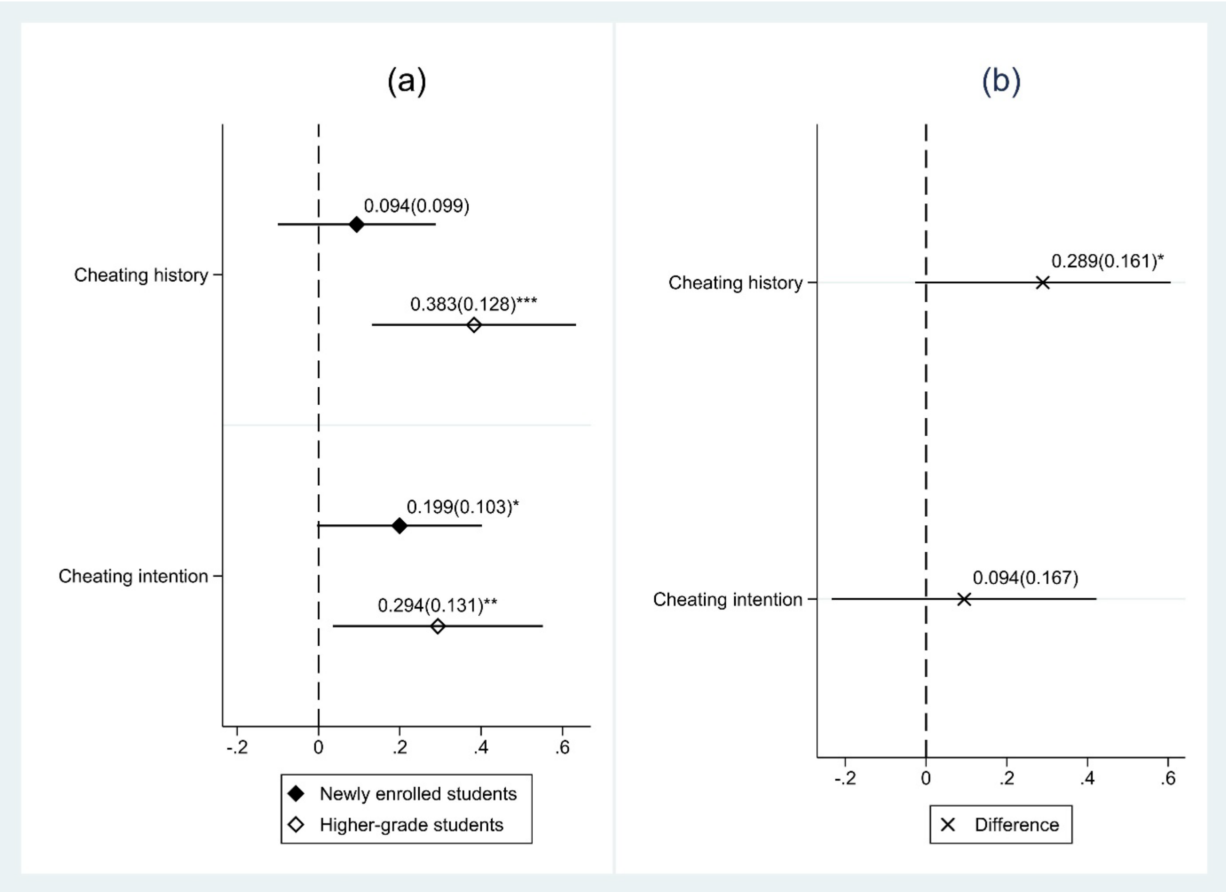

Figure 2.2. Heterogeneous effects of cheating behavior by grade among majority ethnic group

*Note: Figure 2.2a represents the estimated prevalence of respondents who reported affirmative to sensitive statements by grade. Figure 2.2b represents the disparity in cheating behaviors by grade (higher-grade dummy). Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Regarding the heterogeneous effects of academic cheating behavior by ethnicity, higher-grade students are more likely to cheat than newly enrolled students within the majority ethnic group. Figure 2.2 represents the heterogeneous effects of cheating behavior between newly enrolled students and higher-grade students in the majority ethnic group. Specifically, 38.3% of higher-grade students admitted that they had used ChatGPT to cheat, which is over fourfold the prevalence of newly enrolled students reporting the same behavior. Concerning cheating intention among majority ethnic students, both newly enrolled students and higher-grade students had the intention to cheat using ChatGPT, but the difference in cheating intention between these two groups is not statistically significant.

Relevant to the heterogeneous effects of academic cheating behavior by major, only information technology students reported engagement with both cheating history and cheating intention (38.0% and 33.9%, respectively). However, there is no significant difference in cheating history between information technology majors and other majors. Furthermore, information technology students are more likely to have the intention to cheat than medicine and pharmacy students (as shown in Figure A.2).

2.4.3. Robustness check

To examine the stability and reliability of the main results, we conducted additional robustness tests by controlling for multiple covariates and fixed effects at the school level. In addition, we further examine the consistency of heterogeneous effects across subsamples. As shown in Table 2.5 and Figure A.3, the outcomes of robustness tests validate the consistency of our results.

Table 2.5. Robustness test

	Estimated prevalence			
	(1)	(2)	(3)	(4)
Cheating history *(n=924)*	0.237***	0.210***	0.234***	0.204***
	(0.068)	(0.066)	(0.068)	(0.066)
Cheating intention *(n=919)*	0.216***	0.219***	0.216***	0.215***
	(0.069)	(0.067)	(0.069)	(0.066)
Covariates		*Yes*		*Yes*
Fixed effects *(school-level)*			*Yes*	*Yes*

*Note: Column (1) presents the coefficient of treatment effect without covariates and fixed effects. Column (2) presents the coefficient of treatment effect with covariates and no fixed effects. Column (3) presents the coefficient of treatment effect with no covariates and fixed effects. Column (4) presents the coefficient of treatment effect with covariates and fixed effects included. Covariates include age, gender, ethnicity, grade, social association membership, and part-time job engagement. Fixed effects at the school level. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

2.5. Discussion

By using the indirect questioning approach via a list experiment, our findings show that students conceal academic cheating behavior in direct questioning. Any confession of academic cheating may subject the student to negative consequences. Cheating is often punishable by failing assignments or exams, academic probation, or even expulsion from academic institutions. Furthermore, students may be concerned about how their peers, teachers, and parents will perceive them if they are identified as cheaters. Admitting to academic cheating can harm their reputation as honest and capable students. Cheating is frequently associated with moral and ethical stigma. Students conceal their cheating to avoid feelings of shame, guilt, or remorse associated with their dishonest behavior. Consequently, respondents understandably conceal truthful answers when directly questioned.

Our subsample analysis highlighted the heterogeneity in AI-powered academic cheating behavior by gender, as male students are more likely to cheat than female students. In terms of pooled sample analysis, our results align with the findings of previous studies (e.g., Mohd Salleh et al., 2013; Yazici et al., 2023). Gender disparities in moral attitude and risk-taking tendencies possibly cause heterogeneous effects in cheating behavior between male students and female students. Regarding the moral attitude, Ip et al. (2018) highlight that male students hold a more forgiving perspective toward acts of academic cheating than their female counterparts. Gender disparity in academic cheating may be attributed to the notion that women, who tend to prioritize social harmony, are less inclined to violate regulations, while men, who often exhibit greater competitiveness, may be more inclined to transgress rules in pursuit of success (Fisher & Brunell, 2014). In a similar vein, Zhang et al., (2018) reveal that female students exhibited considerably more negative attitudes toward academic misconduct and demonstrated higher levels of upset when they were detected as cheaters. In terms of risk-taking tendencies, Chala (2021) suggests that the propensity for risk-taking behaviors is comparatively greater in males than in females, on average. Male students may be inclined to engage in academic dishonesty as a means to attain their academic objectives due to their higher propensity for taking risks.

In terms of heterogeneity in cheating behavior by grade, higher-grade students are more likely to cheat than newly enrolled students in the majority ethnic group. Our findings contrast with some previous studies. For instance, Bakar-Corez & Kocaman-Karoglu. (2023) found a higher level of academic dishonesty among master students than among Ph.D. students. In a similar vein, Lord Ferguson et al. (2022) highlighted that the prevalence of academic dishonesty is higher among undergraduates than graduates. Importantly, we found that the cheating history of each gender differs substantially across grades. Although male students are more likely to cheat by using ChatGPT in the pooled sample, our subsample analysis shows that no significant difference in cheating history by gender exists among higher-grade students. Conversely, there was a substantial difference in cheating history by gender among newly enrolled students, as the prevalence of cheating among males is strongly dominant. Specifically, female students seem to change their cheating behaviors over time, as they are more likely to cheat in higher grades, as opposed to male students who consistently report cheating history across grades.

Academic-related pressure and peer effects might lead higher-grade students to be more likely to cheat than their counterparts. First, academic-related pressure is usually high for juniors and seniors, particularly in their final academic years. Higher-grade students may engage in academic dishonesty because they perceive it as the band-aid solution to achieve their goals, which are heightened expectations and future career prospects (Ababneh et al., 2022). Additionally, the final academic years are often especially stressful due to the accumulation of coursework, exams, and deadlines. To meet academic requirements, students might cheat to alleviate the stress of managing multiple courses and assignments (Amigud & Lancaster, 2019; Costley, 2019). Specifically, Orok et al., (2023) reveal that fear of failure is the most popular reason for engaging in academic dishonesty as 77% of respondents reported. Second, higher-grade students might be more likely to engage in academic cheating due to the peer dishonesty effect. For instance, Zhao et al. (2022) reveal that the peer dishonesty effect has a strong positive relationship with academic cheating as observing peers engaging in academic misconduct potentially reinforces the idea that cheating is an effective solution to achieve academic objectives without detection of educational institutions. In a similar vein, Lucifora & Tonello, (2015) found that peer effect influences significant academic cheating behaviors among students as the likelihood of cheating increases in case educational institutions loosen the level of class monitoring systems. During the academic journey, the probability of witnessing peer cheating might increase among higher-grade students, potentially influencing them to follow their peers to violate academic integrity under the assistance of AI.

2.6. Conclusion

2.6.1. Summary of findings

This study has provided valuable insights into academic cheating in the era of AI growth. Although AI applications can be valuable educational tools, they also pose associated risks to academic integrity. By exploring a sample of 1,386 Vietnamese undergraduates via the list experiment to minimize social desirability bias, we found a significant misreporting magnitude in responses to AI-powered academic cheating behaviors among undergraduates. Specifically, the prevalence of cheaters observed via list experiments is almost threefold the prevalence of cheaters observed via direct questioning. Regarding the heterogeneous effect of AI-powered academic cheating behaviors among subsamples, we observed that female students are more likely to cheat in the later grades, while male students engage in academic cheating in all grades. In addition, academic cheating is more popular in the final academic years among the majority ethnic group.

2.6.2. Implications

Based on our findings, we suggest both theoretical implications and practical implication that safeguard academic integrity. In terms of theoretical implications, academic cheating should be measured via the indirect questioning method, as students reasonably conceal their truthful answers due to the sensitivity of cheating issues. Educational policies for promoting academic integrity are effective only if cheating behaviors are accurately examined.

In terms of practical implications, male students and higher-grade students of majority ethnicity must be well managed, as these groups showed a higher prevalence of AI-powered academic cheating. In addition, our subsample analysis shows that female students are also more likely to engage in academic dishonesty in higher grades; therefore, educational institutions should implement stringent management policies for these students during their final academic years. To prevent AI-powered cheating while leveraging the advantages of AI in education, it is necessary to apply concurrently supportive solutions and prevention solutions. Regarding supportive solutions, educational institutions should, for instance, offer counseling services to students dealing with stress, anxiety, or other personal issues that may facilitate academic dishonesty, in addition to more intensive orientation programs designed to educate students about the proper use of AI to harness the potential of AI-powered academic cheating but keep improving the learning effectiveness for students. Regarding preventional solutions, educational institutions should further consider investing in advanced monitoring systems to detect AI-powered academic cheating. Simultaneously, the implementation of adaptive assessment methods including randomization, dynamic question generation, and algorithmic modifications is necessary to mitigate the possibility of academic dishonesty facilitated by AI.

2.6.3. Limitations

While this study contributes to the understanding of AI-powered academic cheating in education, it is important to acknowledge the remaining limitations. Because several graduate schools refused to participate, our study is limited to only four specific graduate schools. The generalizability of findings to other student populations, educational backgrounds, or major contexts may be restricted. To address these limitations, further research, methodological improvement, and cross-disciplinary cooperation are needed to deeply investigate academic cheating behavior in the era of accelerated AI.

Chapter 3. Unveiling noncompliance with pesticide practice disciplines among farmers

3.1. Introduction

Pesticide has the indispensable role in pest management strategies aimed at preserving agricultural productivity and food security (Frisvold, 2019; Gurr et al., 2017; Lee et al., 2019; Rakes et al., 2022). Pesticide spans a wide spectrum of applications, ranging from pest control and disease management to weed suppression, contributing significantly to the optimization of agricultural production systems worldwide. For example, Lu et al. (2017) conducted field experiments to evaluate the effectiveness of different pesticide formulations in controlling aphid infestations in wheat crops. Their findings demonstrated that certain pesticide treatments significantly reduced aphid populations, leading to notable improvements in crop yields. Other scholars such as Prager et al. (2020) conducted meta-analyses of pesticide efficacy across various crop systems, reaffirming the importance of pesticides in mitigating yield losses caused by pests.

In addition to pest control, pesticides contribute to the preservation of crop quality, ensuring that agricultural commodities meet safety and market standards. Singh et al. (2019) investigated the impact of pesticide applications on grain quality in maize crops, focusing on reducing mycotoxin contamination. Furthermore, Liu et al. (2021) explored the effects of pesticide use on fruit quality attributes, such as color, firmness, and nutrient content. Their findings indicated that judicious pesticide applications could improve fruit quality parameters, enhancing marketability and consumer acceptance.

The economic implications of pesticide use extend beyond crop protection to encompass broader considerations of farm profitability and livelihoods. Jat et al. (2019) revealed that pesticide use led to significant increases in wheat yields and farm income, highlighting the economic benefits associated with pest management practices. In addition, Yu et al. (2021) emphasized the complex interplay between economic incentives, knowledge dissemination, and access to resources in shaping farmers' pesticide use decisions.

Despite the crucial role of pesticides in modern agriculture, misuse of pesticides leads to severe environmental degradation and adverse consequences for human health. Importantly, pesticide misuse can lead to the contamination of soil, water, and air, causing significant environmental pollution (Abbou et al., 2024; Adil et al., 2023; Berg et al., 2012; Dowling et al., 2019; Huat et al., 2014; Kenko et al., 2024; Leong et al., 2020; Mathis et al., 2022; Schäfer et al., 2019; Zhou et al., 2019). Moreover, exposure to pesticide residues causes various human health issues, including cancers, neurological disorders, reproductive problems, and developmental abnormalities (Berni et al., 2021; Costa et al., 2021; Han et al., 2017; Msibi et al., 2021; Pardo et al., 2020; Rani et al., 2021; Zanchi et al., 2023). Importantly, Boedeker et al. (2020) reveal that pesticides cause over 385 million cases of acute pesticide poisoning each year, with an estimated 11,000 deaths.

To prevent environmental and health risks due to pesticide misuse, a large body of literature has empirically examined the pesticide application behaviors of farmers. Many studies attempt to quantify the prevalence of pesticide misuse and its determinants. For instance, Sun et al. (2019) found that pesticide misuse commonly occurred in rice, fruit, and vegetable crops in China. Schreinemachers et al. (2020) quantify pesticide overuse among 1000 farmers in Laos, Cambodia, and Vietnam and report that 76.6% of vegetable producers overuse pesticides. In the context of pesticide application timing, Möhring et al. (2020) reveal that over one-third of pesticide applications take place earlier than recommended. Pesticide misuse is attributable to various factors, including inadequate pest management knowledge among farmers, limited access to reliable agricultural extension services, dissemination of misleading information, and the absence of reliable prediction and forecasting mechanisms (Hashemi & Damalas, 2010; Li et al., 2023; Sharifzadeh et al., 2019; Sun et al., 2019; Toleubayev et al., 2011; Xu et al., 2021).

To address the issue of biased responses that persists in previous studies which employed direct questioning to investigate pesticide practices, we apply list experiments in a case study with 786 green tea farmers in Thai Nguyen Province, Vietnam. By leveraging a randomized design and an indirect questioning technique, a list experiment effectively mitigate common biases in response to pesticide-related sensitive questions. Regarding the study area, Thai Nguyen province is a compelling case study for pesticide application because of, as elaborated below, the existence of thousands of small-scale tea farms. Our research contributes to a precise understanding of noncompliance with pesticide practice regulations among farmers. Based on these results, we suggest information dissemination strategies that effectively promote safe pesticide practices and thus foster sustainable agricultural production.

This study seeks to answer the two following research questions:

(i) Do farmers under-report noncompliance with pesticide practice regulations in direct responses?

(ii) Does farmers' noncompliance with pesticide practice regulations differ by gender?

The remainder of this chapter is structured as follows: Section 3.2 provides background information about pesticide practice regulations which are investigated in this study. Section 3.3 presents details of the study sites and data collection process. Section 3.4 describes the research methodology and the experiment design. Section 3.5 presents the main findings. Section 3.6 provides discussions based on empirical findings. The last section provides conclusions and explores the potential implications for promoting good agricultural practice.

3.2. Background of investigated pesticide regulations

This chapter investigates farmers' noncompliance with two principal pesticide practice regulations: The Pre-Harvest Interval regulation and Pesticide garbage storage regulation. This subsection introduces the detailed information about these regulations and determinants of why farmers potentially hide their noncompliance.

3.2.1. Pre-harvest Interval

The Pre-Harvest Interval (PHI) is a critical concept in agriculture and pesticide application practices, specifically referring to the minimum period that must elapse between the application of a pesticide and the harvest of the crop intended for consumption or commercial use. This interval is mandated to ensure that residues of the pesticide have sufficiently degraded or dissipated to safe levels that comply with regulatory standards and do not pose health risks to consumers. PHI values vary depending on factors such as the type of pesticide used, the crop being treated, environmental conditions, and regulatory requirements set by governmental agencies. It is determined through extensive testing and scientific studies that assess the persistence and potential health impacts of pesticide residues in agricultural products.

As specified in criteria CB 7.4.1 of GLOBALG.A.P (Global Good Agricultural Practice) standards 2019, Farmers must strictly adhere to PHI guidelines to ensure compliance with food safety regulations and to minimize the risk of pesticide residues exceeding safe levels in harvested crops. Violating PHI regulations can lead to significant consequences, including the rejection of agricultural products during inspection, potential health hazards to consumers, and legal ramifications for non-compliance. In practice, managing the PHI involves careful planning of pesticide application schedules, monitoring environmental conditions, and adhering to recommended waiting periods before harvest. This diligence not only ensures compliance with regulatory standards but also supports sustainable agricultural practices by safeguarding food quality and consumer safety throughout the agricultural production cycle. Thus, the PHI plays a crucial role in integrating effective pest management strategies with responsible stewardship of agricultural resources and public health protection.

In this study, I focus on investigating whether farmers under-report their noncompliance with PHI regulations or not. Farmers may potentially hide their noncompliance with PHI regulations for a wide range of reasons, rooted in social and economic determinants. In terms of economic pressure, adhering to PHI regulations often requires farmers to delay harvesting, which can result in financial losses if crops are not harvested at the optimal time. Farmers may prioritize immediate economic gains over compliance with PHI regulations, especially if they face financial strain or market pressures to deliver crops on schedule. Next, admitting to noncompliance with PHI regulations could damage a farmer's reputation within their community or among agricultural stakeholders. There may be a reluctance to disclose noncompliance due to concerns about social stigma, loss of trust, or negative perceptions from peers, buyers, or regulatory authorities.

3.2.2. Pesticide garbage storage regulations.

Pesticide garbage can pose significant environmental and health risks due to the toxic nature of pesticides and their residues. Improper disposal or storage of pesticide containers, residues, and other waste materials can lead to various harmful effects. In terms of environmental contamination, pesticide residues can leach into soil, surface water, and groundwater, contaminating natural ecosystems. This contamination can adversely affect soil fertility, water quality, and aquatic organisms, disrupting local biodiversity and ecosystem functioning. Regarding risks to human health, exposure to pesticide residues through inhalation, ingestion, or dermal contact can pose serious health risks to farmers, nearby communities, and wildlife. Pesticides are designed to be toxic to pests and can also harm humans and non-target organisms if not handled and disposed of correctly.

Under the criteria CB 7.9 of GLOBALG.A.P standards 2019, pesticide garbage storage regulations require agricultural producers to maintain dedicated storage facilities for empty pesticide containers, residues, and other waste materials. These facilities must be secure, well-ventilated, and equipped with measures to prevent leaks, spills, or unauthorized access. Containers must be rinsed thoroughly, punctured to prevent re-use, and stored in a manner that prevents cross-contamination with other agricultural inputs or waste streams. Compliance with GLOBALG.A.P standards necessitates the implementation of strict inventory management and record-keeping practices for pesticide waste. Producers are required to maintain accurate records of pesticide applications, container usage, and disposal activities, which are subject to audit and verification by certification bodies.

In this study, I focus on investigating whether farmers under-report their noncompliance with storage regulations (by leaving pesticide garbage on farms or water sources). Farmers may potentially hide or not truthfully disclose their pesticide garbage storage practices for several reasons, which often stem from a combination of regulatory and social concerns. First, farmers may fear repercussions or penalties from regulatory authorities if they are found to be in violation of pesticide waste management regulations. Non-compliance could result in fines, legal action, or restrictions on agricultural activities. As a result, some farmers may choose to conceal improper storage practices to avoid scrutiny or consequences.

Regarding social concerns, there may be a stigma associated with admitting to improper or inadequate pesticide waste management practices. Farmers may fear damage to their reputation or social standing within their community if it is known that they are not adhering to recommended or mandated environmental and human health standards.

3.3. Data collection

3.3.1. Study sites

The case study focuses on the pesticide application practices of 786 small-scale green tea farmers in Thai Nguyen, a province in the northern mountainous area of Vietnam. Fig. 2 shows the map of our study site. The province has a total area of 3,563 km^2 with nine administrative districts. With hilly terrain, a temperature range of 16-34°C, and average annual rainfall from 2,000-2,500 mm, Thai Nguyen has suitable natural conditions for green tea production. The province is well known as the tea crop center of the country, as it accounts for 23.4% of the country's green tea production (General Statistics Office of Vietnam, 2021).

Green tea production in Thai Nguyen presents a compelling case study of farmers' pesticide practice compliance for several reasons. First, pesticide residue issues in Vietnam's tea products raise serious concerns for both producers and consumers. Ly et al. (2022) indicate that 64.7% of Vietnamese tea samples are pesticide-contaminated, and the average residue concentration reached 298 µg kg-1 (ranked 3rd out of 5 countries in the study). Given the increasing competition in the tea industry, the Vietnamese government has striven to improve the quality of tea products and enhance international recognition. However, noncompliance with pesticide regulations not only negatively affects human health and the natural environment but can also result in trade barriers and restrictions on Vietnam's tea exports. Noncompliance can lead to rejected shipments or increased scrutiny, which can harm the reputation and market access of the country (Dou et al., 2015; Ferro et al., 2015; Hejazi et al., 2022). The empirical findings of this study can provide valuable suggestions to policymakers for developing appropriate strategies to overcome current problems regarding pesticide practices in tea production.

Second, managing good agricultural practices among producers has become a challenging task for governments. In the context of a large green tea production area with thousands of small-scale tea producers in Thai Nguyen, managing compliance with pesticide regulations can indeed be difficult. These problems emphasize the necessity of analyzing effective extension disseminators that have a vital role in promoting good agricultural practices to achieve sustainable development.

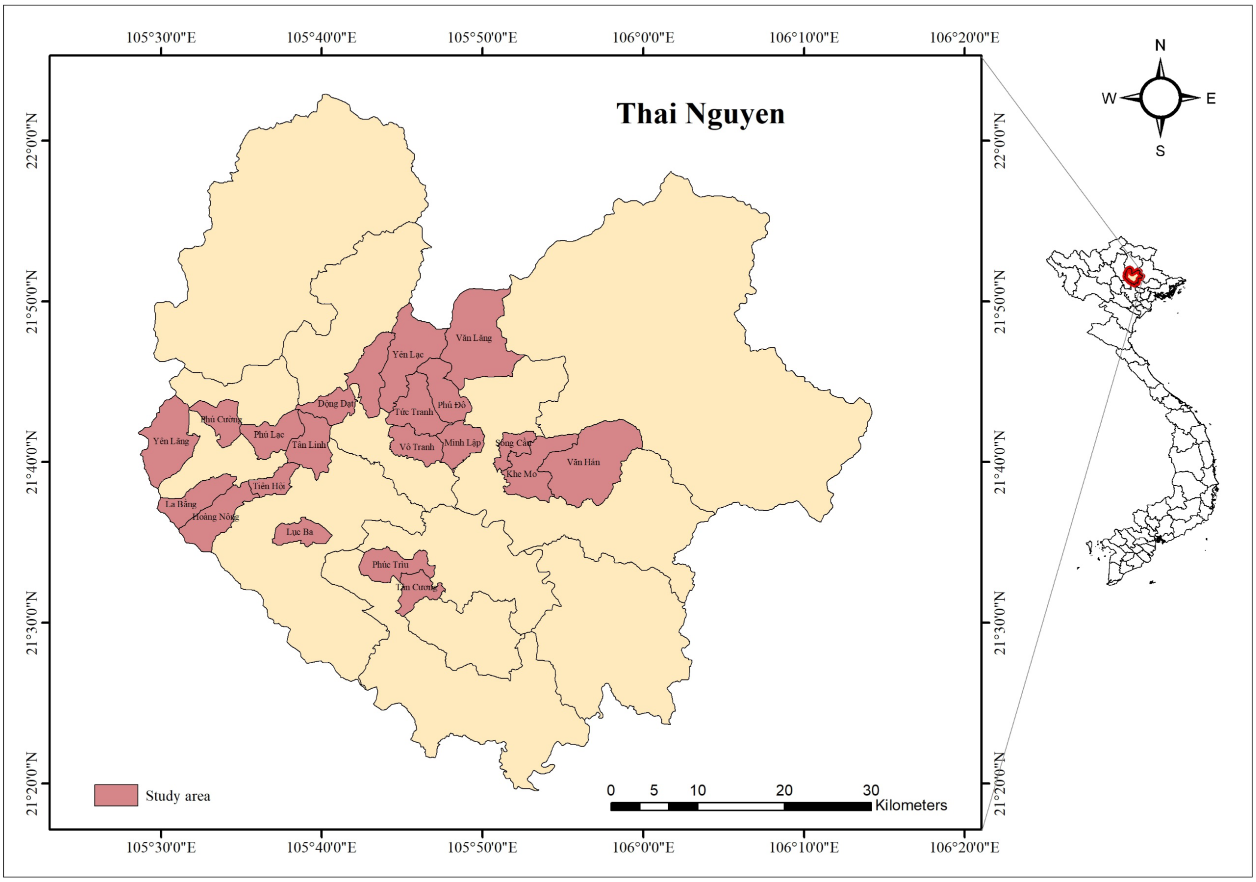

Figure 3.1. Map of research areas

3.3.2. Random sampling

From April to May 2023, we conducted this list experiment with 786 green tea farmers in Thai Nguyen. First, we selected four district-equivalent administrative units that are central regions for green tea production with national brands, namely, Thai Nguyen City, Dong Hy, Phu Luong, and Dai Tu (Table 3.1). We then sampled 20 communes with the largest tea production area where the number of communes in each district is proportional to the district-level tea production area. Figure 3.1 maps the location of selected communes.

Next, we randomly selected 45 tea households that have tea farms from two nonneighboring villages with major tea production areas in each of the 20 communes, leading to an initial list of 900 households. From each household, we interviewed and conducted list experiments with one household representative who engaged intensively in the family's tea production (hereafter, tea farmers) . Due to the unavailability of household representatives on the interview days, our final sample contains 876 tea farmers, equivalent to a 97% participation rate.

Table 3.1. The planted area of green tea by districts in Thai Nguyen

District-level area	2017	2018	2019	2020	2021
Dai Tu	6,336	6,337	6,342	6,433	6,602
Phu Luong	4,032	4,053	4,09	4,025	4,194
Dong Hy	3,326	3,601	3,796	3,846	3,856
Dinh Hoa	2,561	2,607	2,647	2,695	2,694
Pho Yen town	1,613	1,654	1,689	1,687	1,677
Thai Nguyen city	1,641	1,607	1,545	1,531	1,492
Vo Nhai	1,208	1,245	1,265	1,305	1,315
Song Cong city	670	660	654	628	448
Phu Binh	262	264	253	249	167
Total	21.649	22.027	22.282	22.399	22.445

(Source: Thai Nguyen statistical yearbook 2021)

3.3.3. Descriptive statistics

Table 3.2 provides descriptive statistics of the tea farmers in the sample. On average, tea farmers are approximately 50 years old with 7 years of national education. Female farmers account for 58% of respondents. Most tea farmers are small-scale producers with an average farm size of 0.284 ha . It is essential to precisely examine noncompliance behavior in pesticide practices among respondents who mostly have medium to low education and are small-scale tea growers. In particular, the proportion of farmers that adopt good agricultural practices through membership in VietGAP groups remains at 18%. Cooperative participation was even lower, as the participation rate in the sample was only 12.6%.

3.4. Methodology

3.4.1. Experiment design

This study includes 2 separate phases. Phase 1 (list experiment) aimed to investigate the prevalence of noncompliance with pesticide regulations among tea farmers via the indirect questioning approach. Next, Phase 2 (direct questioning) helps to investigate the prevalence of noncompliance with pesticide regulations among tea farmers via the basic direct questioning approach. Table 3.3 describes the experimental design of Chapter 3.

Table 3.2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Age *(years)*	876	50.558	10.631	25	83
Gender *(male dummy)*	876	.420	.494	0	1
Ethnicity *(ethnic minority dummy)*	876	.283	.451	0	1
Education *(years)*	876	7.170	2.519	0	16
Co-operative membership *(member dummy)*	876	.126	.332	0	1
VietGAP membership *(member dummy)*	876	.180	.385	0	1
Farm size *(ha)*	876	.284	0.241	.01	3
Tea revenue *(mill. VND)*	876	25.449	47.519	0	780

Phase 1 (list experiment) includes the participation of all groups. Respondents were randomly assigned to control group treatment groups. Figure 3.2 describes the treatment assignment of this study. Respondents in the control group received a list containing four nonsensitive statements. Treatment group 1 received a list that included a similar list of nonsensitive statements as the control group and an additional sensitive statement that helps to measure the prevalence of farmers who break PHI regulations. Similarly, the list for treatment group 2 is equipped with an additional sensitive statement along with four nonsensitive statements from the control group to measure the prevalence of farmers who break Pesticide garbage storage regulations.

In Phase 1, all the respondents were required to indicate only the total number of statements that they agreed with. Consequently, we can calculate the average response value of each group. We then captured the prevalence of noncompliance with PHI regulation by calculating the difference in the average response value between the control group and treatment group 1. Similarly, the prevalence of farmers who break Pesticide garbage storage regulation is calculated by the difference in the average response value between the control group and treatment group 2.

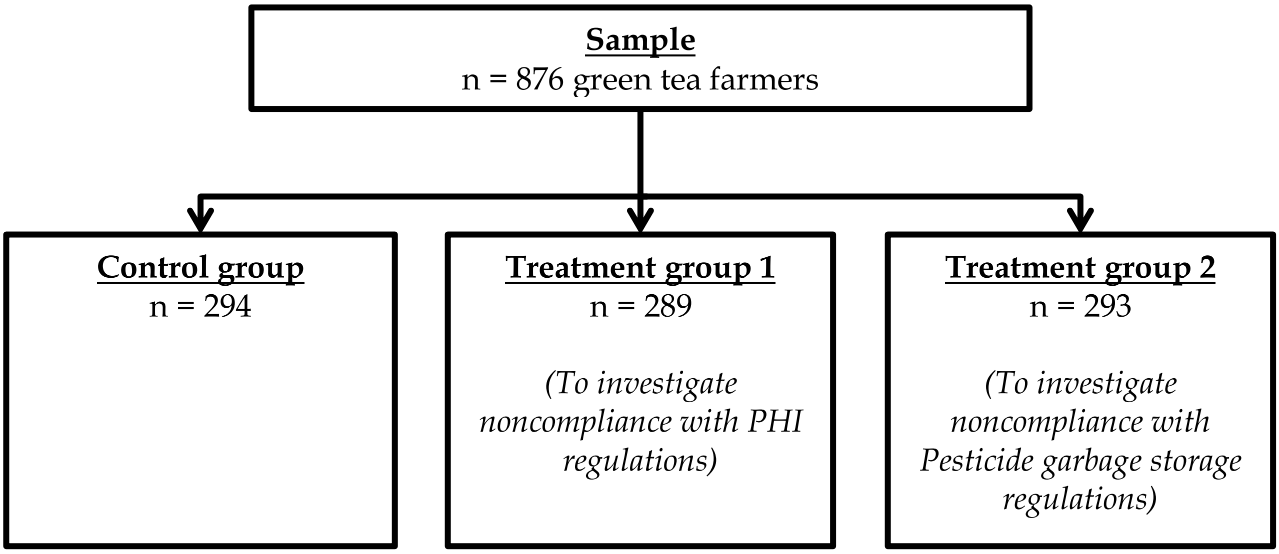

Figure 3.2. Treatment assignment of Chapter 3

Next, we investigated farmers' noncompliance via direct questioning (Phase 2). Only respondents in the control group participated in this phase. To guarantee the accuracy of the outcomes, Phase 2 includes participation only by respondents in the control group because these respondents did not engage with sensitive statements during the list experiment, as opposed to respondents in the treatment groups. In Phase 2, respondents in the control group were required to answer only "yes" or "no" for noncompliance with two investigated regulations. By doing so, we can observe the prevalence of farmers who break PHI regulation and Pesticide garbage storage regulation respectively via direct questioning.

3.4.2. Validation

List experiments must satisfy three key assumptions: (1) random assignment, (2) no liars, and (3) no design effect (Imai, 2011). These three assumptions are empirically validated in this subsection.

Table 3.4 shows the outcomes of balance check between the control and treatment groups of the list experiments. Based on these outcomes, we can confirm that the randomization in both surveys was guaranteed.

Regarding ceiling or floor effect, I confirm that there was no presence of these effects in this experiment. Table B.1 describes the proportion of response values. No ceiling or floor effect exists since the proportions of all affirmative or all negative responses in both surveys were under 4% of the total responses.

Table 3.3. Experiment design of Chapter 3

Procedure	Control group	Treatment group 1	Treatment group 2
Phase 1 (List experiment)	Please indicate HOW MANY statements you agree with. • *You worn masks and gloves when spraying pesticide in the last 12 months* • *You supported other households during the harvest period in the last 12 months* • *You sold roasted tea to other provinces in the last 12 months* • *You expanded the tea farm size in the last 12 months*	Please indicate HOW MANY statements you agree with. • *You worn masks and gloves when spraying pesticide in the last 12 months* • *You supported other households during the harvest period in the last 12 months* • *You sold roasted tea to other provinces in the last 12 months* • *You expanded the tea farm size in the last 12 months* • *You violated **PHI regulation** of the pesticide manufacturer in the last 12 months*	Please indicate HOW MANY statements you agree with. • *You worn masks and gloves when spraying pesticide in the last 12 months* • *You supported other households during the harvest period in the last 12 months* • *You sold roasted tea to other provinces in the last 12 months* • *You expanded the tea farm size in the last 12 months* • *You left **pesticide waste** such as bags and bottles in farms or water sources in the last 12 months*
Phase 2 (Direct questioning)	Please answer (YES/NO) to the following question: • *Did you violate the **PHI regulation** of the pesticide manufacturer in the last 12 months?* Please answer (YES/NO) to the following question: • *Did you leave **pesticide waste** such as bags and bottles in farms or water sources in the last 12 months?*	Not required to participate	Not required to participate

Regarding design effect, there was no presence of a design effect in this experiment. Table B.1 describes the outcomes of design effect tests.

Table 3.4. Balance check of Chapter 3

	C	T1	T2	T1-C	T2-C
Age *(years)*	50.70 [10.35]	50.70 [10.50]	50.28 [11.06]	.01 (0.86)	-.42 (.88)
Gender *(male dummy)*	.43 [.50]	.42 [.49]	.41 [.49]	-.02 (.04)	-.02 (.04)
Ethnicity *(minority dummy)*	.28 [.45]	.27 [.45]	.29 [.46]	-.01 (.04)	.01 (.04)
Education *(years)*	7.03 [2.41]	7.34 [2.54]	7.14 [2.60]	.30 (.21)	.11 (.21)
Co-operatives *(member dummy)*	.12 [.32]	.14 [.35]	.12 [.32]	.02 (.03)	-.00 (.03)
VietGAP Group *(member dummy)*	.19 [.39]	.19 [.39]	.17 [.37]	-.00 (.03)	-.02 (.03)
Farm size *(ha)*	.27 [.17]	.29 [.26]	.29 [.28]	.02 (.02)	.02 (.02)
Tea revenue *(mills. VNĐ)*	24.69 [36.94]	28.27 [65.70]	23.43 [33.58]	3.59 (4.41)	-1.26 (2.91)
Observations	294	289	293	583	587

*Note: Standard deviations in square brackets. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

3.4.3. Empirical model

With the key assumptions of our experimental design validated, we applied the model in Equation 3 to estimate the prevalence of noncompliance behaviors in pesticide practice regulations:

$$Y_{ic} = \alpha_3 + \tau_3 T_{ic} + \mathbf{X_{ic}}\zeta + \theta_c + \eta_{ic} \qquad (3)$$

Y_{ic} represents the response value, i.e., the total number of agreed statements of respondent i in commune c. T_{ic} represents binary treatment variables (0 for the control group and 1 for the treatment group). τ_3 is the regression coefficient associated with each treatment, which is equivalent to the difference in response value between the control group and treatment group. $\mathbf{X}$ is a vector of respondent-level covariates including age, gender, ethnicity, education, cooperative membership, VietGAP group membership, farm size, and tea revenue. θ_c denotes the commune fixed effects, which capture unobserved commune-specific characteristics, and η_{ic} is the error term.

In terms of misreporting, we evaluate the misreporting level of respondents between the list experiment and direct questioning. To accomplish this, we directly compare the estimated prevalence of sensitive treatments from the list experiment with the prevalence obtained from direct questioning by performing the immediate form of a two-sample t-test with unequal variances.

Equation 4 shows the model that we applied to evaluate the heterogeneous effect in the subgroups:

$$Y_{ic} = \alpha_4 + \tau_4 T_{ic} + \beta D_{ic} + \kappa D_{ic} \cdot T_{ic} + \mathbf{X}_{ic}\zeta + \theta_c + \eta_{ic} \qquad (4)$$

κ indicates the difference in the prevalence of sensitive treatments among subgroups. D_{ic} is the subgroup dummy of respondent i in commune c for the characteristic of interest. For example, when we analyze the heterogenous response between the female and male, D_{ic} is equal to 1 for female respondents and 0 otherwise (i.e., a female dummy).

3.5. Results

This section shows the principal findings of our research. First, we present the outcomes of both the list experiment and direct questioning, along with the magnitude of misreporting observed between these two methods of questioning. Subsequently, we provide a comprehensive description of the heterogeneous effects observed among subgroups.

3.5.1. Main results

The prevalence of noncompliance with pesticide regulations increases significantly in the list experiment. Table 3.5 depicts the prevalence of noncompliance with pesticide regulations and the misreporting level between the two questioning methods. Regarding direct questioning, only a minor portion of respondents reported their noncompliance behavior with PHI and pesticide waste storage regulations (10.5% and 11.2%, respectively).

However, the prevalence of noncompliance behaviors in both regulations rose dramatically in the list experiment. Specifically, the prevalence of farmers who violate PHI regulations increased nearly threefold to 28.4%, and the prevalence of farmers who violate pesticide waste storage regulations doubled to 21%. The results suggest that PHI noncompliance was especially sensitive among tea farmers, as the difference in PHI noncompliance between indirect and direct questioning was 17.9 percentage points (significant at the 1% level).

Conversely, the difference in the prevalence of pesticide waste storage between the list experiment and the direct questioning method is not significant despite the substantial difference in point estimates between the two questioning methods.

Table 3.5. Main results of Chapter 3

	Mean of responses		Estimated prevalence		Difference (1)-(2)
	Control	Treatment	List Experiment (1)	Direct Questioning (2)	
PHI noncompliance	2.619 [.627]	2.903 [.915]	.284*** (.065)	.105 [.308]	.179*** (.068)
Observations	*294*	*289*	*583*	*294*	
Pesticide waste storage noncompliance	2.619 [.627]	2.829 [.886]	.210*** (.063)	.112 [.316]	.098 (.066)
Observations	*294*	*293*	*587*	*294*	

*Note: Standard deviations in square brackets. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

3.5.2. Sub-sample analysis

First, regarding heterogeneity by gender, the prevalence of noncompliance with PHI among female farmers is dramatically higher. Figure 3.3 shows that the prevalence of female farmers who reported noncompliance with PHI regulations was 43.7%, while only 7% of male respondents reported the same behavior. The difference between the two groups is 36.6 percentage points, which is significant at the 1% level. In terms of pesticide waste storage behavior and farmers' trust, no significant differences exist between male and female respondents.

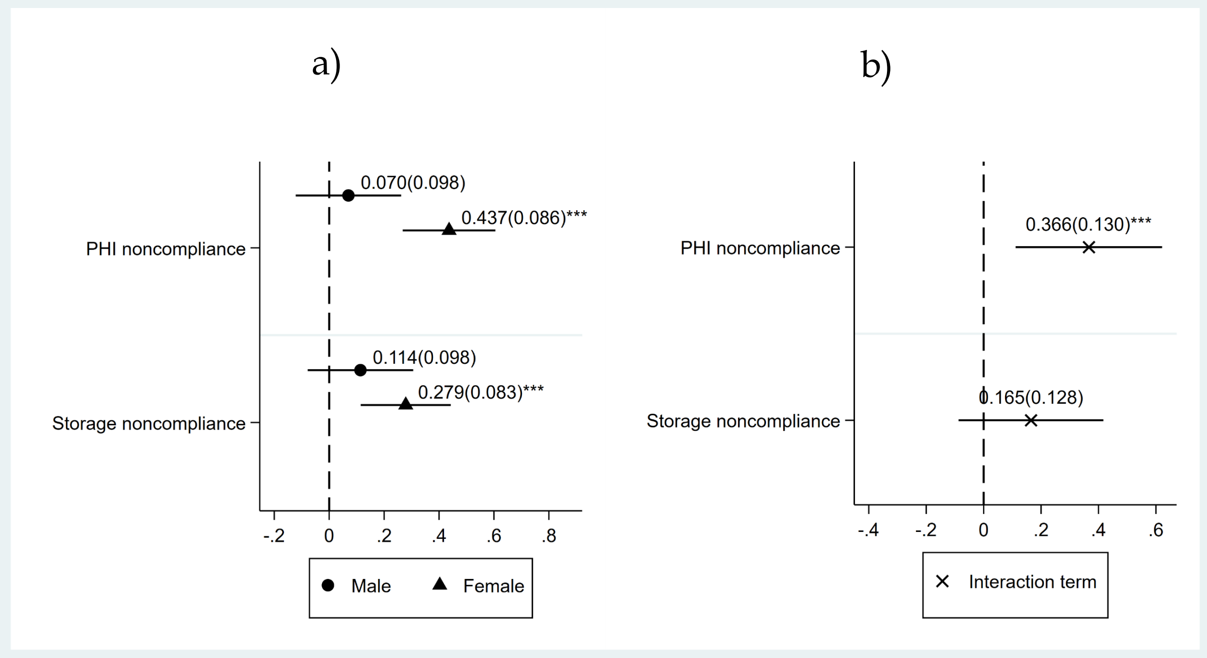

Figure 3.3. Heterogeneous effects by gender

*Note: Figure 3.3a represents the prevalence of pesticide practice noncompliance by gender. Figure 3.3b represents the disparity in pesticide practice noncompliance by gender. Standard deviations in square brackets. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

3.5.3. Robustness check

To examine the stability and reliability of the main results, we conducted additional robustness tests by controlling for multiple covariates and fixed effects at the school level. In addition, we further examine the consistency of heterogeneous effects across subsamples. As shown in Table 3.6 and Figure B.1, the outcomes of robustness tests validate the consistency of our results.

Table 3.6. Robustness test

	(1)	(2)	(3)	(4)
PHI noncompliance (*n=583*)	.284***	.279***	.288***	.287***
	(.065)	(.065)	(.065)	(.065)
Pesticide waste storage noncompliance (*n=587*)	.210***	.208***	.207***	.205***
	(.063)	(.064)	(.063)	(.063)
Covariates		*Yes*		*Yes*
Fixed effects			*Yes*	*Yes*

*Note: Column (1) presents the coefficient of treatment effect without covariates and fixed effects. Column (2) presents the coefficient of treatment effect with covariates and no fixed effects. Column (3) presents the coefficient of treatment effect with no covariates and fixed effects. Column (4) presents the coefficient of treatment effect with covariates and fixed effects included. Covariates include age, gender, ethnicity, education, co-operatives membership, VietGAP group membership, farm size, and tea revenue. Fixed effects at the commune level. Robust standard errors in parenthesis. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

3.6. Discussion

Farmers may under-report non-compliance with the Pre-harvest Interval (PHI) disciplines due to various factors, including economic pressures, lack of awareness, fear of consequences, and social stigma.

First, regarding economic pressure, timely harvesting is crucial for maximizing yields and profits. Farmers may face financial constraints or market pressures that incentivize them to harvest crops before the recommended PHI period, especially if they fear potential losses due to pest damage, adverse weather conditions, or market fluctuations. As a result, they may prioritize immediate economic gains over adherence to pesticide regulations.

Second, lack of awareness might affect the farmers' noncompliance with PHI. Some farmers may not fully understand or appreciate the importance of adhering to PHI requirements. They may lack access to information about pesticide labels, safety regulations, and the potential health and environmental risks associated with pesticide residues. Without adequate knowledge or training, farmers may inadvertently overlook or underestimate the significance of PHI disciplines, leading to non-compliance.

Third, farmers may fear negative repercussions, such as financial penalties, legal sanctions, or damage to their reputation, if they are found to be non-compliant with PHI regulations. In some cases, regulatory enforcement may be inconsistent or perceived as ineffective, leading to a culture of non-compliance or lax enforcement. As a result, farmers may be tempted to under-report or conceal instances of non-compliance to avoid scrutiny or punishment.

Furthermore, there may be social norms or peer pressure that discourage farmers from reporting or acknowledging instances of non-compliance with PHI disciplines. Farmers may feel pressure to conform to prevailing practices or expectations, even if they conflict with regulatory requirements. Additionally, there may be reluctance to acknowledge mistakes or admit to non-compliance due to concerns about reputational damage or social stigma.

The subsample analysis reveal that the PHI noncompliance being significantly higher among female farmers compared to male farmers can indeed be influenced by time constraints. Female farmers often face multiple responsibilities, including childcare, household chores, and agricultural work, which can create significant time constraints and competing demands on their time. For instance, Lamontagne-Godwin et al., (2017) highlighted that female farmers have less access to extension support compared to their counterparts. Under these circumstances, female tea growers might shorten the minimum required time for the crop harvest.

3.7. Conclusions

3.7.1. Summary of findings

This study provides valuable insights into farmers' misreporting behavior in pesticide practice noncompliance and trust in local extension supporters. By rigorously examining a sample of 876 tea farmers using the indirect questioning approach, we successfully reveal misreporting behavior among respondents. Primarily, our results indicate that local farmers significantly conceal their noncompliance with PHI regulations in the direct questioning approach. The prevalence of PHI noncompliance rose by approximately threefold in the list experiment, indicating that PHI noncompliance is a highly sensitive issue among the local community. Reasonably, disclosure of noncompliance can subject farmers to legal actions and penalties. Furthermore, reporting noncompliance behaviors negatively affects the perception of the public, leading to reputational damage. In terms of farmers' trust in extension supporters, farmers substantially overreport their trust in local extension supporters, including VHs and LEOs. Respondents might fear potential repercussions for openly expressing their support for government officers, especially in authoritarian or repressive regimes. In the context of local communities, it may be considered impolite or disrespectful to freely discuss or criticize village leaders. Respondents might adhere to these norms and avoid expressing their true views.

3.7.2. Implications

We suggest two implications based on our findings. First, extension supporters need to strictly manage compliance with PHI regulations among female farmers. Based on the list experiment's outcomes, female farmers are more likely to not conform to PHI regulations than male farmers. Addressing the time constraints faced by female farmers requires gender-sensitive approaches that recognize and address the unique challenges they face. This includes providing support mechanisms such as access to childcare services, labor-saving technologies, and extension services tailored to the needs of female farmers. By reducing the burden of unpaid care work and empowering female farmers to manage their time more effectively, agricultural policies and programs can help mitigate gender disparities in PHI noncompliance and promote more inclusive and sustainable farming practices.

Second, governments and policymakers should develop suitable management strategies to maximally utilize the effectiveness of LEOs for senior farmers. Our findings indicate that LEOs have considerable influence among senior farmers. Sustainable agriculture encompasses more than just a set of practices; it also involves a constant interplay and balancing act between responsible authorities in the community. The more effective the information communication method applied, the more sustainable development goals that are achieved

3.7.3. Limitations

Despite extensive research on the topic, the current study is limited by its scope, which may restrict the generalizability of the findings. Due to the limited sample size, our study focused on only pesticide regulations, namely, PHI and pesticide waste storage. Other pesticide regulations, such as pesticide mixture formulas, spraying techniques, or volume of spray compliance, need to be deeply examined. In addition, future research can expand the scope to other extension supporters, such as pesticide retailers or peer farmers, to further examine the effectiveness of diversified extension information disseminators.

Chapter 4. Unveiling farmers' trust in extension services

4.1. Introduction

Agricultural extension services play a crucial role in supporting agricultural development, enhancing productivity, and promoting sustainable farming practices. These supporters serve as a vital link between farmers and the latest agricultural knowledge, technologies, and practices (Hörner et al., 2022; Gichohi-Wainaina et al., 2021; Kondylis et al., 2017). Specifically, Davis et al. (2016) highlights the significant positive impact of extension services on farmers' adoption of improved agricultural practices and technologies, leading to increased yields and incomes. In addition, agricultural extension services contribute to building farmers' capacity and resilience in the face of challenges such as climate change and environmental degradation. For instance, Simpson et al., (2018) highlight the role of extension in promoting climate-smart agricultural practices and enhancing farmers' adaptive capacity. By providing tailored advice and training, extension services help farmers adopt sustainable farming techniques that mitigate environmental risks and promote long-term agricultural sustainability.

In terms of business, agricultural extension services play a vital role in facilitating market access and promoting value chain development in agriculture. Berg et al., (2017) indicates that effective extension programs can help farmers access markets, improve market information, and enhance their bargaining power. Extension services assist farmers in diversifying their products, improving product quality, and meeting market demands, thereby contributing to increased agricultural incomes and rural livelihoods.

Examining farmers' trust in local extension services is a critical endeavor within agricultural research and development. Trust plays a pivotal role in shaping the effectiveness and impact of extension services on farming communities. Importantly, trust in extension services establishes a foundation of credibility and reliability, influencing farmers' decisions regarding the adoption of new technologies, implementation of recommended practices, and engagement in collaborative initiatives aimed at enhancing agricultural productivity and sustainability (Birner et al., 2018). Moreover, trust facilitates meaningful relationships between farmers and extension agents, fostering open communication, mutual understanding, and effective knowledge transfer. This relational aspect not only strengthens the delivery of agricultural information and support but also cultivates a conducive environment for personalized assistance tailored to local contexts and specific farming challenges (Pretty, 2018).

Previous studies further investigated effective sources of information for improving proper pesticide practices. However, the results remain disputed. For instance, Madaki et al., (2023) and Jallow et al. (2017) argue that farmers tend to rely on pesticide recommendations from peer farmers and village leaders rather than those provided by governmental extension agencies. In a similar vein, Pan et al. (2021) suggest disseminating pesticide knowledge through peer farmers and pesticide sellers rather than extension officers, as they find that the former decreases pesticide expenditure compared to the latter. In contrast, Fan et al. (2015) indicate that farmers report a higher belief in extension workers than in peer farmers or local village leaders. Wuepper et al., (2021) highlight that public extension services encourage effectively farmers to use more preventive measures.

Although these insights are valuable, there are important issues with the findings from the surveys using direct questioning typically employed in previous studies. respondents could intentionally misreport their truthful beliefs due to political fear or community relationships (Nicholson & Huang, 2022). As a result, the outcomes of previous studies that employed the direct questioning method might be biased due to social desirability.

To address above-mentioned research gaps among previous studies, this study aims to investigate the over-report among farmers about trust in extension services. Furthermore, heterogeneous effects in trust among subsamples are carefully examined to deepen understanding about credibility of extension services among local communities.

To attain above research objectives, this study seeks to answer the two following research questions:

(i) Do farmers over-report trust in extension services in direct responses?

(ii) Do farmers' trust in extension services differ by age?

The remainder of this chapter is structured as follows: Section 4.2 provides background information about extension services investigated in this study. Section 4.3 presents details of the study sites and data collection process. Section 4.4 describes the research methodology and the experiment design. Section 4.5 presents the main findings. Section 4.6 provides discussions based on empirical findings. The last section provides conclusions and explores the potential implications for enhancing the effectiveness of agricultural extension services among local communities.

4.2. Background of extension services

This chapter aims to investigate farmers' trust in two agricultural extension services including Village Heads and Local Extension Officers. This subsection introduces the detailed information and roles of above-mentioned extension services.

4.2.1. Village Heads

The Village Heads (VHs) are local representatives who hold the leadership position within a village. These local leaders typically perform a wide range of duties including administrative management, implementation of government policies and programs, maintenance of public order, provision of basic public services such as healthcare and education at the local level, and representing the interests of the community to higher levels of government (Cheo et al., 2022; Schneider & Sircar, 2024). VHs also play a crucial role in grassroots governance, community development, and ensuring the well-being and advancement of their respective villages or communes within the broader framework of administrative structure (Xi & Ratigan, 2024). Regarding appointment procedure, VHs are often appointed through election by villagers or appointment by higher authorities, depending on local administrative regulations and practices.

In terms of agricultural extension support, the role of a VH is pivotal in facilitating the dissemination of agricultural knowledge, promoting sustainable practices, and fostering rural development within their respective communities. First, VHs often work as advocates for agricultural development initiatives tailored to local needs. They collaborate with extension workers and agricultural experts to identify relevant technologies, best practices, and innovative methods that can enhance agricultural productivity and sustainability. By leveraging their local knowledge and authority, VHs facilitate the adoption of new techniques among farmers, thereby contributing to improved yields, income generation, and food security within their communities. Second, VHs play a crucial role in facilitating communication and cooperation among farmers, extension agents, and local government authorities. They organize community meetings, workshops, and training sessions where farmers can acquire new skills, receive technical advice, and access resources provided through agricultural extension programs. This facilitative role not only enhances knowledge dissemination but also strengthens social cohesion and collective action towards achieving agricultural development goals.

Moreover, VHs serve as key stakeholders in advocating for policies and resources that support agricultural development at the local level. They liaise with higher levels of government and external organizations to secure funding, infrastructure, and other necessary resources essential for the implementation of agricultural extension activities. Through their leadership and advocacy efforts, VHs contribute to creating an enabling environment where farmers can thrive, innovate, and contribute to the sustainable growth of agricultural production systems.

4.2.2. Local Extension Officers

Local Extension Officers (LEOs) are government-appointed officers who play a critical role in agricultural extension services at the grassroots level. They serve as pivotal figures in local communities, playing diverse and essential roles aimed at enhancing agricultural productivity, rural development, and community welfare (Gichohi-Wainaina et al., 2021; Wiréhn, 2024). Their primary responsibility lies in facilitating the dissemination of agricultural knowledge, best practices, and technological innovations among farmers and rural dwellers. Through direct engagement with farmers, LEOs provide advisory services on crop cultivation techniques, livestock management, pest and disease control, and sustainable agricultural practices (Afzal et al., 2016; Indraningsih et al., 2023). By promoting the adoption of modern agricultural methods and technologies, LEOs contribute significantly to improving agricultural productivity and ensuring food security within their respective communities.

Beyond agricultural advisory roles, LEOs function as brigde for rural development initiatives transfer. They collaborate closely with local government agencies, non-governmental organizations, and community-based organizations to identify and address socio-economic challenges facing rural areas. This collaborative effort extends to the implementation of community development projects aimed at improving infrastructure, access to clean water, healthcare services, education, and other essential amenities. By mobilizing resources and fostering partnerships, LEOs play a crucial role in fostering inclusive and sustainable development that uplifts the quality of life for rural residents.

4.3. Data collection

In this study, I utilized our experiment with the same sample size as described in Chapter 3. The study sites and data collection process are described in section 3.2. Please refer to this section for detailed information.

4.4. Methodology

4.4.1. Experiment design

As mentioned above, we applied cross-randomization with the same sample size as Chapter 3. Figure 4.1 describes the cross-randomization between Chapter 3 and Chapter 4. In general, the treatment assignment of Chapter 4 is completely independent of the treatment assignment of Chapter 3.

The study in this chapter similarly includes 2 separate phases. Phase 1 (list experiment) aimed to investigate the farmers' trust in extension services via the indirect questioning approach. Next, Phase 2 (direct questioning) helps to investigate the farmers' trust in extension services via the basic direct questioning approach. Table 4.1 describes the experimental design of Chapter 4.

Phase 1 (list experiment) includes the participation of all groups. Respondents were randomly assigned to control group treatment groups. Respondents in the control group received a list containing four nonsensitive statements. Treatment group 1 received a list that included a similar list of nonsensitive statements as the control group and an additional sensitive statement that aims to measure the farmers's trust in VHs. Similarly, the list for treatment group 2 is equipped with an additional sensitive statement along with four nonsensitive statements from the control group to measure the prevalence of farmers who trust LEOs.

In Phase 1, all the respondents were required to indicate only the total number of statements that they agreed with. Consequently, we can calculate the average response value of each group. We then captured the prevalence of farmers who trust VHs by calculating the difference in the average response value between the control group and treatment group 1. Similarly, the prevalence of farmers who trust LEOs is calculated by the difference in the average response value between the control group and treatment group 2.

Next, we investigated farmers' trust in extension services via direct questioning (Phase 2). Only respondents in the control group participated in this phase. To guarantee the accuracy of the outcomes, Phase 2 includes participation only by respondents in the control group because these respondents did not engage with sensitive statements during the list experiment, as opposed to respondents in the treatment groups. In Phase 2, respondents in the control group were required to answer only "yes" or "no" for noncompliance with two investigated regulations. By doing so, we can observe the prevalence of farmers who trust VHs and LEOs respectively via direct questioning.

4.4.2. Validation

This subsection validated the list experiment based on three key conditions: (1) random assignment, (2) no liars, and (3) no design effect.

In terms of random assignment, Table 4.2 shows the outcomes of balance check between the control and treatment groups of the list experiments. Based on these outcomes, we can confirm that the randomization in both surveys was guaranteed.

Regarding ceiling or floor effect, I confirm that there was no presence of these effects in this experiment. Table C.1 describes the proportion of response values. No ceiling or floor effect exists since the proportions of all affirmative or all negative responses in both surveys were under 4% of the total responses.

Regarding design effect, there was no presence of a design effect in this experiment. Table C.1 describes the outcomes of design effect tests.

4.4.3. Empirical model

With the key assumptions of our experimental design validated, we applied the model in Equation 5 to estimate the prevalence of noncompliance behaviors in pesticide practice and trust in sensitive extension supporters:

$$E_{ic} = \alpha_5 + \tau_5 H_{ic} + \mathbf{X}_{ic}\nu + \theta_c + \pi_{ic} \qquad (5)$$

E_{ic} represents the response value, i.e., the total number of agreed statements of respondent i in commune c. H_{ic} represents binary treatment variables (0 for the control group and 1 for the treatment group). τ_5 is the regression coefficient associated with each treatment, which is equivalent to the difference in response value between the control group and treatment group. $\mathbf{X}$ is a vector of respondent-level covariates including age, gender, ethnicity, education, cooperative membership, VietGAP group membership, farm size, and tea revenue. θ_c denotes the commune-level fixed effects, which capture unobserved commune-specific characteristics, and π_{ic} is the error term.

In a subsequent analysis, we evaluate the misreporting level of respondents between the list experiment and direct questioning. To accomplish this, we directly compare the estimated prevalence of sensitive treatments from the list experiment with the prevalence obtained from direct questioning by performing the immediate form of a two-sample t-test with unequal variances.

Equation 6 shows the model that we applied to evaluate the heterogeneous effect in the subgroups:

$$E_{ic} = \alpha_6 + \tau_6 H_{ic} + \iota S_{ic} + \mu S_{ic} \cdot T_{icl} + \mathbf{X}_{ic}\nu + \theta_c + \pi_{ic} \qquad (6)$$

μ indicates the difference in the prevalence of sensitive treatments among subgroups. S_{ic} is the subgroup dummy of respondent i in commune c for the characteristic of interest. For example, when we analyze the heterogenous response between the female and male, S_{ic} is equal to 1 for female respondents and 0 otherwise (i.e., a female dummy).

4.5. Results

4.5.1. Main results

Respondents substantially overreported their trust in pesticide recommendations from VHs and LEOs when directly asked. Table 4.3 indicates the proportions of respondents who trust pesticide recommendations from VHs and LEOs, and the disparities between the two measures reflect farmer overreporting behavior. Regarding the direct approach, most respondents report trust in pesticide recommendations from both VHs and LEOs (82.8% and 89.2%). Unfortunately, the prevalence of farmers trusting VHs fell by over one-third to 53.6% in the list experiment. Similarly, the prevalence of farmers trusting LEOs' recommendations fell 28% to 64.3% in the indirect approach. The magnitude of misreporting regarding farmers' trust in VHs and LEOs remains high, suggesting that both extension supporters are extremely sensitive authorities among local communities.

Table 4.1. Experiment design of Chapter 4

Procedure	Control group	Treatment group 1	Treatment group 2
Phase 1 (List experiment)	Please indicate HOW MANY statements you agree with. • *You believe that spraying pesticides on rainy days decreases the effectiveness of pesticide* • *You believe that spraying a lot of pesticides will harm the environment* • *You believe that spraying pesticides decreases productivity* • *You believe that pesticide causes no harm to human health*	Please indicate HOW MANY statements you agree with. • *You believe that spraying pesticides on rainy days decreases the effectiveness of pesticide* • *You believe that spraying a lot of pesticides will harm the environment* • *You believe that spraying pesticides decreases productivity* • *You believe that pesticide causes no harm to human health* • *You believe the pesticide recommendation from* ***VHs***	Please indicate HOW MANY statements you agree with. • *You believe that spraying pesticides on rainy days decreases the effectiveness of pesticide* • *You believe that spraying a lot of pesticides will harm the environment* • *You believe that spraying pesticides decreases productivity* • *You believe that pesticide causes no harm to human health* • *You believe the pesticide recommendation from* ***LEOs***
Phase 2 (Direct questioning)	Please answer (YES/NO) to the following question: • *Do you believe the pesticide recommendation from* ***VHs****?* Please answer (YES/NO) to the following question: • *Do you believe the pesticide recommendation from* ***LEOs****?*	Not required to participate	Not required to participate

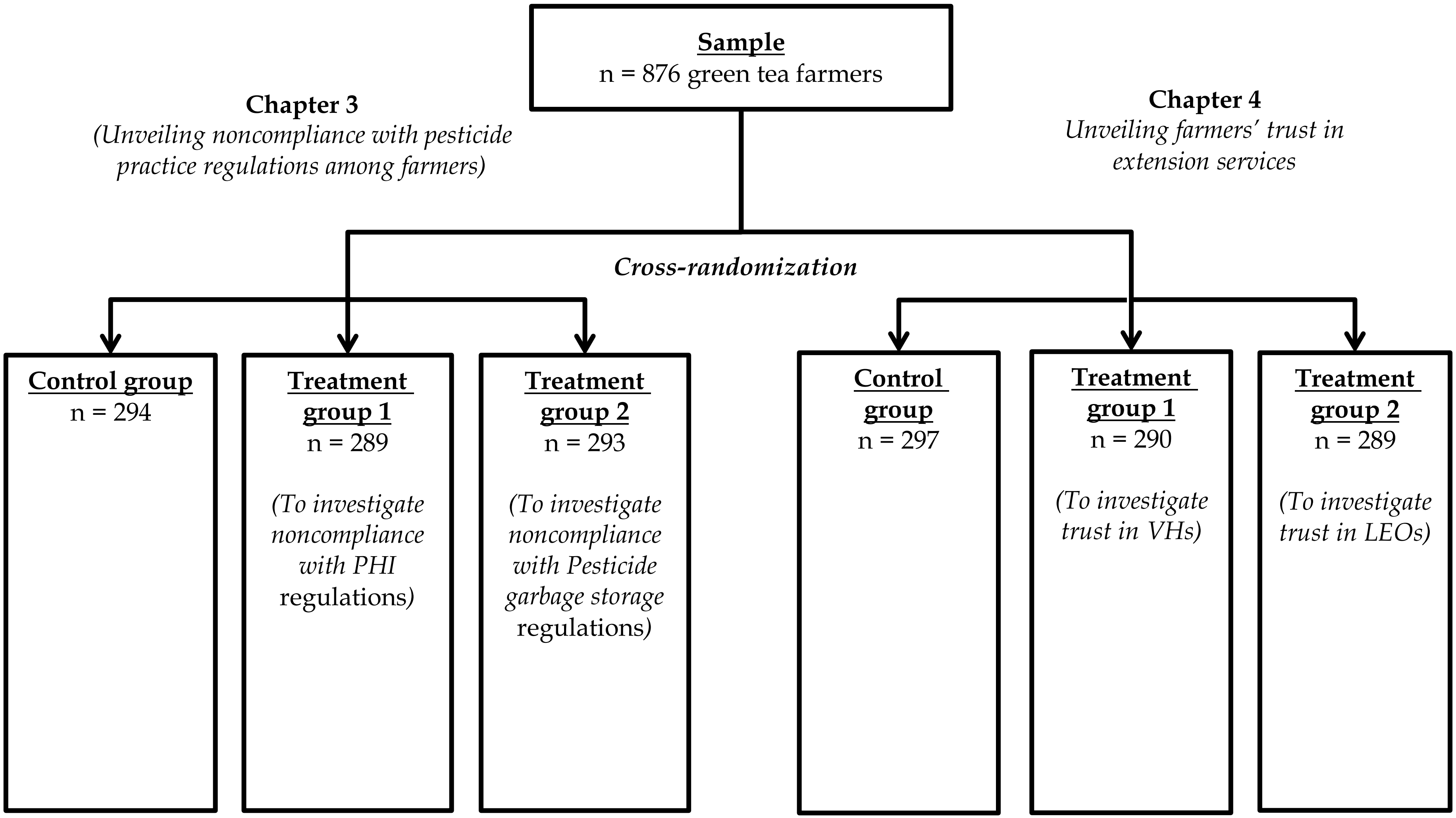

Figure 4.1. Cross-randomization between Chapter 3 and Chapter 4

Table 4.2. Balance check of Chapter 4

	C	T1	T2	T1-C	T2-C	F-test
Age *(years)*	51.41 [10.85]	49.89 [10.55]	50.36 [10.47]	-1.53* (.88)	-1.05 (.88)	1.59
Gender *(male dummy)*	.40 [.49]	.43 [.50]	.43 [.50]	.02 (.04)	.03 (.04)	.24
Ethnicity *(minority dummy)*	.28 [.45]	.28 [.45]	.29 [.46]	.00 (.04)	.02 (.04)	.13
Education *(years)*	7.23 [2.54]	7.12 [2.57]	7.17 [2.46]	-.11 (.21)	-.06 (.21)	.14
Co-operatives *(member dummy)*	.14 [.35]	.16 [.36]	.08 [.28]	.02 (.03)	-.06** (.03)	3.77
VietGAP Group *(member dummy)*	.16 [.37]	.22 [.42]	.16 [.37]	.06* (.03)	.00 (.03)	2.4
Farm size *(ha)*	.29 [.22]	.29 [.28]	.27 [.22]	.01 (.02)	-.02 (.02)	.54
Tea revenue *(mills. VNĐ)*	24.14 [33.43]	29.14 [61.07]	23.09 [44.14]	5.00 (4.05)	-1.05 (3.23)	1.34
Observations	297	290	289	587	586	

*Note: Standard deviations in square brackets. Standard errors in parenthesis. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

4.5.2. Sub-sample analysis

In terms of trusting LEOs among young farmers and senior farmers, elderly farmers report a substantially higher prevalence of trust. Figure 4.2 shows the heterogeneity in noncompliance behavior with pesticide regulations and trust in pesticide information sources between young farmers (under 43 years old) and senior farmers (over 58 years old)[7]. A total of 83.5% of senior farmers reported trust in LEOs, while only 45.7% of young farmers reported the same choice. The difference in trust between the two groups is 37.8 percentage points, which is significant at the 5% level. There are no heterogeneous effects in VHs trust or noncompliance behaviors of farmers between young and senior farmers.

[7] We defined young farmers as respondents with age in the 1st quartile (n=226) and senior farmers as respondents with age in the 4th quartile (n=226)

Notably, senior farmers trust LEOs more than they trust VHs. Figure 4.3 indicates that 83.5% of senior respondents trust LEOs, while VHs only received support from 54.9% of senior respondents. The magnitude of the difference is 28.6 percentage points, which is significant at the 5% level, suggesting that LEOs have substantially more influence among senior farmers.

Table 4.3. Main results of Chapter 4

	Mean of responses		Estimated prevalence		
	Control	Treatment	List Experiment (1)	Direct Questioning (2)	Difference (1)-(2)
Trust VHs	2.471 [.626]	3.007 [.844]	.536*** (.061)	.828 [.378]	-.293*** (.065)
Observations	*297*	*290*	*587*	*297*	
Trust LEOs	2.471 [.626]	3.114 [.832]	.643*** (.061)	.892 [.311]	-.249*** (.064)
Observations	*297*	*289*	*586*	*297*	

*Note: Standard deviations in square brackets. Standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

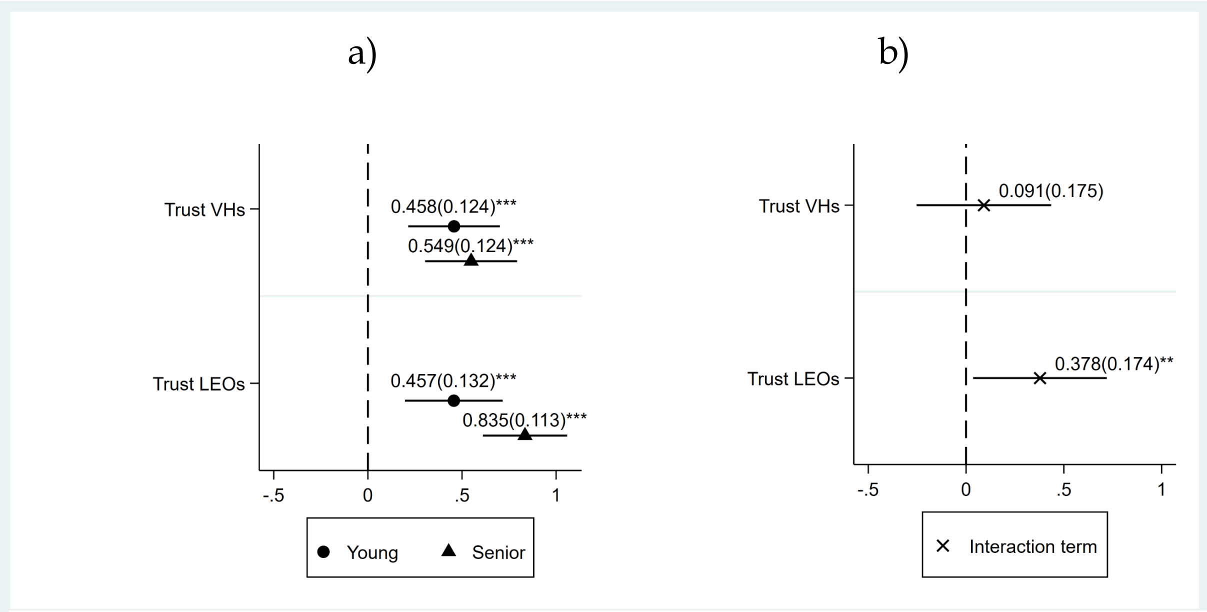

Figure 4.2. Heterogeneous effects by age.

*Note: Figure 4.2a represents the prevalence of farmers trust in extension services. Figure 4.2b represents the disparity of farmers' trust in extension services by age group. Standard deviations in square brackets. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

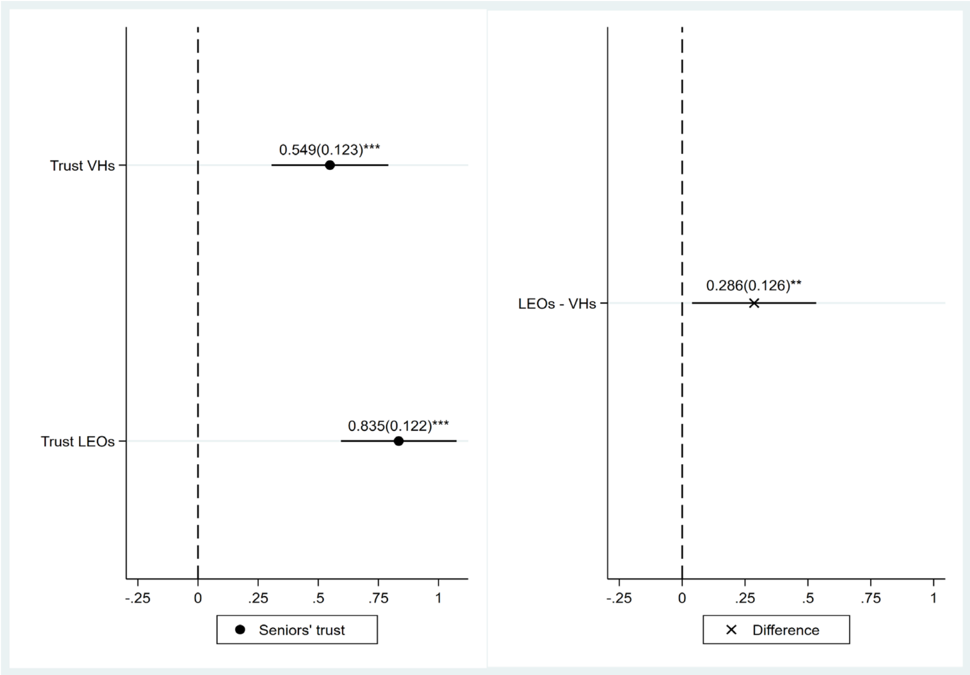

Figure 4.3. Heterogeneous effects on seniors' trust.

*Note: Figure 4.3a represents the prevalence of senior farmers' trust in extension services. Figure 4.3b represents disparity in senior farmers' trust. Standard deviations in square brackets. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

4.5.3. Robustness check

To examine the stability and reliability of the main results, we conducted additional robustness tests by controlling for multiple covariates and fixed effects at the school level. In addition, we further examine the consistency of heterogeneous effects across subsamples. As shown in Table 4.4 and Figure C.1, the outcomes of robustness tests validate the consistency of our results.

Table 4.4. Robustness test

	(1)	(2)	(3)	(4)
Trust VHs (*n=587*)	.536***	.541***	.535***	.537***
	(.061)	(.062)	(.062)	(.062)
Trust LEOs (*n=586*)	.643***	.638***	.642***	.636***
	(.061)	(.061)	(.062)	(.062)
Covariates		*Yes*		*Yes*
Fixed effects			*Yes*	*Yes*

*Note: Column (1) presents the coefficient of treatment effect without covariates and fixed effects. Column (2) presents the coefficient of treatment effect with covariates and no fixed effects. Column (3) presents the coefficient of treatment effect with no covariates and fixed effects. Column (4) presents the coefficient of treatment effect with covariates and fixed effects. Covariates include age, gender, ethnicity, education, co-operatives membership, VietGAP group membership, farm size, and tea revenue. Fixed effects at the commune level. Robust standard errors in parenthesis. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

4.6. Discussion

To explain why farmers tend to over-report trust in both VHs and LEOs due to political fear, several key insights emerge from the literature and findings of this thesis. The phenomenon of over-reporting trust can be understood through the lens of social desirability bias, where respondents alter their responses to align with perceived societal norms or expectations, often influenced by political fear or local relationships.

Regarding political fear, this factor might emerge as a potent motivator shaping farmer responses. First, the role of VHs and LEOs as intermediaries between farmers and government policies imbues them with significant influence and authority within rural communities. This authority can create a power dynamic wherein farmers feel compelled to express trust and support, regardless of their true sentiments, to maintain favorable relations or access to essential resources and services. Second, local governance intertwines closely with political affiliations or patronage systems, farmers may fear adverse consequences, such as loss of access to subsidies, loans, or even land tenure security, if they express distrust or criticism of VHs or extension officers perceived to be aligned with ruling parties or authorities.

Next, local relationship potentially distorts the truthful responses of farmers. Rural communities often operate on principles of reciprocity and mutual support. VHs and LEOs are integral to the social fabric, providing not just administrative support but also personal connections and community cohesion. Farmers might feel a sense of obligation or reciprocity towards these figures, leading them to express higher levels of trust than they might genuinely feel. This behavior stems from a desire to maintain harmonious social relationships and to reciprocate the support and assistance received from these local leaders.

The subsample analysis reveals that senior farmers trust LEOs rather than VHs. Expertise and professionalism might be potential factors for this trend. First, LEOs are typically trained professionals with specialized knowledge in agriculture and rural development. They often provide technical advice, training, and support to farmers on agricultural practices, pest management, soil health, and the adoption of new technologies. Senior farmers, who value practical expertise and reliable information to improve their farming practices, may place greater trust in extension officers due to their perceived competence and professional background in agriculture. Our findings present contrasting results with other studies that highlight the superiority of farmer-to-farmer extension approaches to traditional extension services via extension workers, such as BenYishay and Mobarak (2019) or Niu and Ragasa (2018).

The findings also suggest that senior farmers trust LEOs more than young farmers trust these supporters. Limited access to diversified extension sources might affect the extension services selection among senior farmers. Specifically, Senior farmers may perceive these professionals as more accessible and responsive to their needs due to their established presence in the community and potentially longer-standing relationships with extension officers. In contrast, young farmers have the advantage of information accessibility in various extension-supporting channels. They often have a broader network of peers and connections in agricultural production who can provide additional extension information and insights. Furthermore, younger individuals are typically more proficient in navigating the internet and effectively utilizing search strategies. They are more active users in online channels, social media platforms, and e-commerce markets, where they can seek detailed information, recommendations, advice, and opinions from others about agricultural information. Consequently, younger farmers are likely to be less influenced by LEOs since they have a wide range of extension information sources

4.7. Conclusions

4.7.1. Summary of findings

Examining farmers' trust in local extension services is instrumental in promoting community resilience and adaptive capacity in response to dynamic agricultural landscapes. In times of adversity, such as climatic shocks or economic uncertainties, trusted extension services serve as vital sources of guidance, resilience-building strategies, and timely interventions that enable farmers to navigate challenges effectively. By fostering trust, extension services contribute not only to individual farmer empowerment but also to the collective development of rural communities through improved food security, income generation, and sustainable natural resource management practices. Importantly, understanding and enhancing farmers' trust in local extension services is imperative for advancing agricultural development agendas, promoting sustainable farming practices, and ensuring the equitable and impactful delivery of agricultural extension programs tailored to meet the diverse needs of farming populations.

This chapter provides valuable insights into farmers' trust in local extension services. By rigorously examining a sample of 876 tea farmers using the indirect questioning approach, we successfully reveal misreporting behavior among respondents. Primarily, farmers substantially overreport their trust in local extension supporters, including VHs and LEOs. Respondents might fear potential repercussions for openly expressing their support for government officers, especially in authoritarian or repressive regimes. In the context of local communities, it may be considered impolite or disrespectful to freely discuss or criticize village leaders. Respondents might adhere to these norms and avoid expressing their true views.

4.7.2. Implications

This subsection presents the implications based on empirical findings that underscore critical considerations for enhancing the effectiveness and relevance of agricultural extension services, particularly in fostering trust and supporting farmers.

First, the measurement of trust in extension services among farmers should prioritize the use of indirect questioning methods. These approaches, characterized by their ability to mitigate social desirability biases and encourage more candid responses, are essential for obtaining accurate insights into farmers' perceptions and levels of trust. By employing indirect questioning techniques, researchers and practitioners can uncover nuanced factors influencing trust dynamics, such as communication effectiveness, perceived reliability, and responsiveness to farmers' needs.

Second, the role of LEOs emerges prominently as effective supporters for senior farmers within agricultural extension services. LEOs possess intimate knowledge of community contexts, cultural sensitivities, and local agricultural practices. These officers play a pivotal role in delivering tailored advice, facilitating access to resources, and providing ongoing support that addresses the unique challenges faced by senior farmers in adapting to technological advancements and sustainable farming practices. Moreover, local officers' proximity and familiarity with the community enable them to act as trusted intermediaries, bridging communication gaps and ensuring that extension services are responsive to the specific needs and preferences of senior farmers.

4.7.3. Limitations

While the current chapter yields significant insights into farmers' perceptions and reporting on trust in extension services, several key limitations should be recognized to contextualize the study's conclusions within its scope.

First, the findings of this chapter may not be fully generalizable due to the limited scope of its sample size. This limitation restricts the diversity and representativeness of the farmer population studied, potentially skewing the findings toward particular demographics, geographical regions, or farming contexts. Consequently, caution should be exercised in extrapolating these findings to broader populations or different agricultural settings without additional research to validate their applicability.

Second, the study focus on investigating trust in only two types of extension services including VHs and LEOs. this limitation might further constrain the depth and comprehensiveness of its conclusions. Extension services encompass a wide range of stakeholders and support mechanisms within agricultural communities, including peer farmers and input suppliers such as pesticide retailers, whose perspectives on trustworthiness and effectiveness may differ significantly from those of VHs and LEOs. Thus, future research efforts should aim to incorporate a more diverse array of stakeholders to capture a comprehensive understanding of trust dynamics across various facets of agricultural extension.

Chapter 5. Conclusion

5.1. Summary

This dissertation has explored the utility and applicability of list experiments as a methodological tool in social sciences. Through a comprehensive review of the literature and the implementation of multiple list experiments, this research has demonstrated the efficacy of list experiments in eliciting truthful responses on sensitive to mitigate social desirability bias. By employing this innovative indirect questioning technique, this dissertation has delved into sensitive topics in education and agriculture.

This dissertation includes three main objectives. First, this study aims to investigate heterogeneous effects among sub-samples from the list experiment's outcomes. The second research objective is to utilize list experiment in the education sector. The third research objective is to utilize list experiment in the agriculture sector. Based on the three above-mentioned research objectives, three core chapters are designed to attain these research objectives.

Specifically, chapter 2 attains the first research objective using the list experiment to unmask academic cheating behavior in the artificial intelligence era. Although AI applications can be valuable educational tools, they also pose associated risks to academic integrity. By exploring a sample of 1,386 Vietnamese undergraduates via the list experiment to minimize social desirability bias, we found a significant misreporting magnitude in responses to AI-powered academic cheating behaviors among undergraduates. Specifically, the prevalence of cheaters observed via list experiments is almost threefold the prevalence of cheaters observed via direct questioning. Regarding the heterogeneous effect of AI-powered academic cheating behaviors among subsamples, we observed that female students are more likely to cheat in the later grades, while male students engage in academic cheating in all grades. In addition, academic cheating is more popular in the final academic years among the majority ethnic group.

Chapter 3 successfully obtained the second research objective. This chapter investigates the sensitive issues related to pesticide practice in the agriculture sector. By rigorously examining a sample of 876 tea farmers using the indirect questioning approach, we successfully reveal misreporting behavior among respondents. Primarily, our results indicate that local farmers significantly conceal their noncompliance with PHI regulations in the direct questioning approach. The prevalence of PHI noncompliance rose by approximately threefold in the list experiment, indicating that PHI noncompliance is a highly sensitive issue among the local community. Reasonably, disclosure of noncompliance can subject farmers to legal actions and penalties. Furthermore, reporting noncompliance behaviors negatively affects the perception of the public, leading to reputational damage. In terms of farmers' trust in extension supporters, farmers substantially overreport their trust in local extension supporters, including VHs and LEOs. Respondents might fear potential repercussions for openly expressing their support for government officers, especially in authoritarian or repressive regimes. In the context of local communities, it may be considered impolite or disrespectful to freely discuss or criticize village leaders. Respondents might adhere to these norms and avoid expressing their true views.

Chapter 4 successfully attains the third research objective. By applying cross-randomization with the same sample as Chapter 3, this chapter examines farmers' trust in local extension services among agricultural producers. List experiment is employed to minimize social desirability bias caused by local relationships and political fear. Regarding farmers' trust in extension services, the results reveal that farmers substantially overreported their trust in both VHs and LEOs when directly asked. In terms of credibility, LEOs are more effective influencers among senior farmers.

5.2. Implications

This section presents implications based on empirical findings of three core chapters.

First, policymakers should rigorously consider the disparity in gender and age during the policy-making process. Findings of Chapter 2 show that female students are more likely to cheat in the later grades, while male students engage in academic cheating in all grades. In addition, academic cheating is more popular among higher-grade students who usually have higher age compared to newly enrolled students. Chapter 3 highlights that female has a higher prevalence of noncompliance with pesticide practice regulations. In terms of farmers' trust in extension services, chapter 4 found a disparity in farmers' trust in extension services. Specifically, senior farmers trust LEOs more than young farmers trust these extension services. Different genders and age groups may face unique challenges and needs. Gender and age disparities often highlight inequalities in access to resources, opportunities, and outcomes. Addressing these disparities through policy can promote fairness and equal opportunities for all members of society, regardless of gender or age. Policies that recognize and address these differences can effectively target interventions and support systems to mitigate disparities and promote well-being across all segments of the population.

Second, sensitive issues in the education sector and agriculture sector should be well examined via the indirect questioning approach. Employing direct questioning about sensitive topics such as academic cheating, or agricultural practices may lead respondents to provide socially desirable responses. On the other hand, indirect questioning techniques can mitigate social desirability bias by framing questions in a way that reduces the perceived threat to the respondent's self-image or reputation.

5.3. Limitations

While this dissertation contributes to deepening the understanding of the application of list experiments in the education and agriculture sectors, it is important to acknowledge the remaining limitations. This subsection presents the limitations of the core chapters and the dissertation.

Regarding the limitations of core chapters, all three core chapters have limited sample size and treatment. First, Chapter 2 focused on only four specific graduate schools, which may constrain the generalizability of the findings to other student populations, educational backgrounds, or major contexts. Second, Chapter 3 investigates farmers' noncompliance with only two principal pesticide practice regulations, namely, PHI and pesticide waste storage. Other pesticide practice regulations, such as pesticide mixture formulas, spraying techniques, or volume of spray compliance, need to be deeply examined. Third, the study of Chapter 4 focused on only two extension services including VHs and LEOs. Other stakeholders such as pesticide retailers should be further examined to investigate the effectiveness of diversified extension information disseminators.

Regarding the limitation of this dissertation, the external validity of findings needs to be discussed. The findings could be limited to specific education and agriculture sectors of Vietnam. Hence, the extrapolation of the findings should be carried out cautiously.

Appendix for Chapter 2

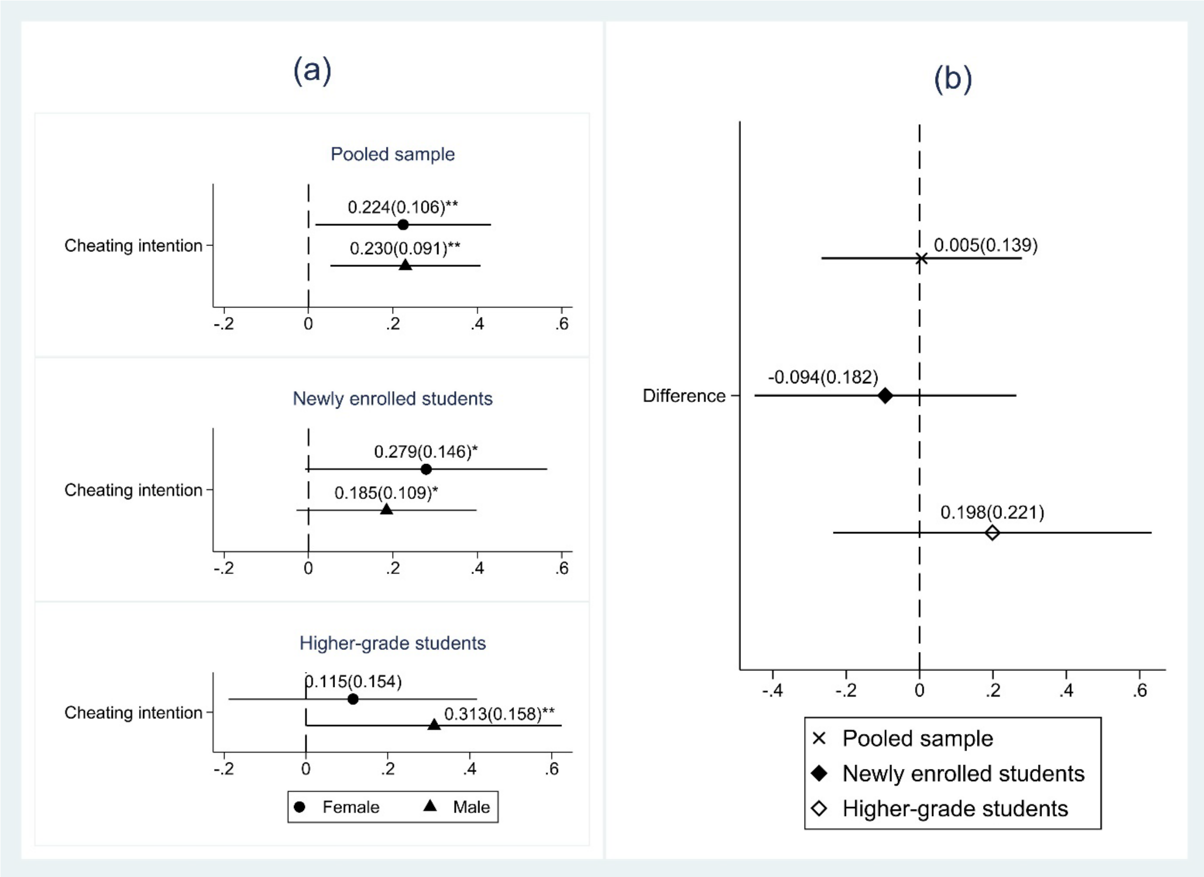

Figure A.1. Heterogeneous effects of the cheating intention by gender.

*Note: Fig A.1a represents represents the estimated prevalence of respondents who reported affirmative for cheating intention by gender. Fig A.1b represents the disparity in cheating intention by gender (male dummy). Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

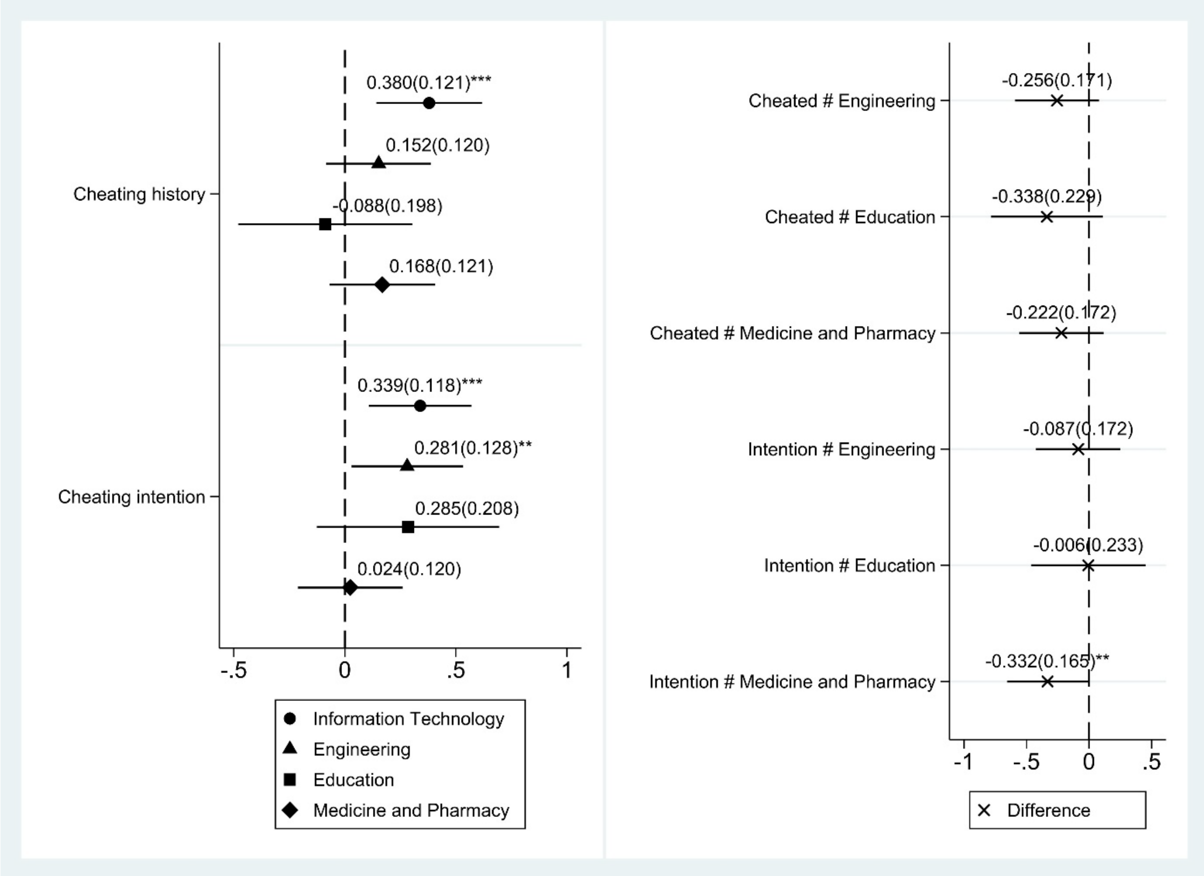

Figure A.2. Heterogeneous effects of cheating behavior by major.

*Note: Figure A.2a represents the estimated prevalence of respondents who reported affirmative to sensitive statements. Figure A.2b represents the disparity in cheating behaviors by major (the major base is Information Technology). Covarites include age, gender, ethnicity, grade, social, and part-time jobFixed effects at the commune level. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

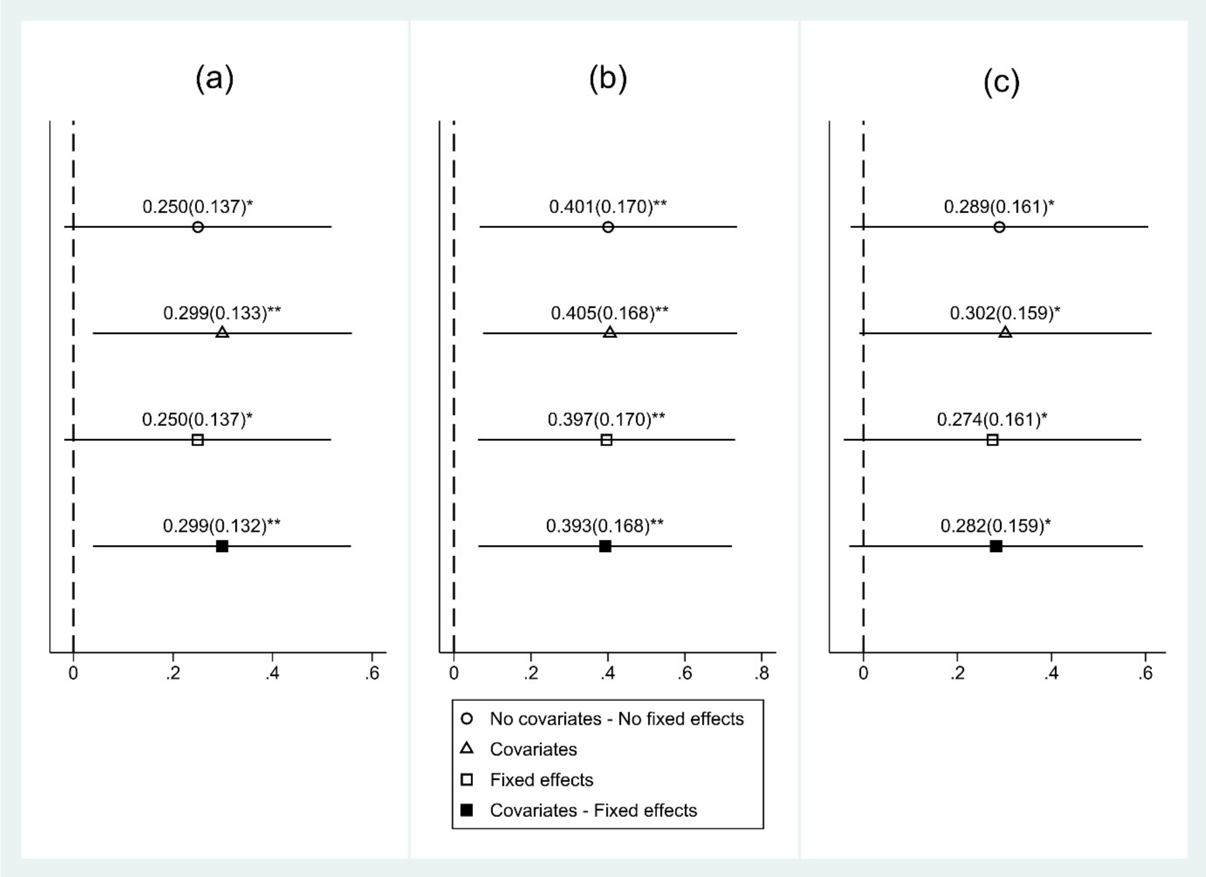

Figure A.3. Subsample robustness tests of Chapter 2

*Note: Figure A.3a represents the heterogeneous effects of cheating history by gender (male dummy). Figure 3.Ab represents the heterogeneous effects of cheating history by gender among newly enrolled students (male dummy). Figure 3.Ac represents the heterogeneous effects of cheating history by grade among students with majority ethnicity (higher-grade dummy). Covarites include age, gender, ethnicity, grade, social, and part-time job. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Table A.1. Distribution of respondents

Graduate school	Total number of undergraduates	Limit of participants	Actual number of participants	Proportion (%)
Engineering	5,228	422	420	30.3
Information Technology	4,993	403	401	28.9
Medicine and Pharmacy	4,749	384	380	27.4
Education	2,354	190	185	13.3
Total	17,324	1,450	1,386	100

Table A.2. Distribution of response values

Response value	Control group		Treatment group 1		Treatment group 2	
	Frequency	Proportion	Frequency	Proportion	Frequency	Proportion
0	37	8.10	35	7.49	38	8.23
1	134	29.32	103	22.06	104	22.51
2	182	39.82	177	37.90	177	38.31
3	82	17.94	114	24.41	99	21.43
4	22	4.81	28	6.00	34	7.36
5	_	_	10	2.14	10	2.16
Total	457	100	467	100	462	100

Table A.3. Design effect test of Chapter 2

Ha: Pr<0	K	Lambda	P>Lambda	#P>Lambda
Treatment Group 1				
Pr(R ,S=0)	0	0.000	1.000	1.000
Pr(R ,S=1)	0	0.000	1.000	1.000
Treatment Group 2				
Pr(R ,S=0)	0	0.000	1.000	1.000
Pr(R ,S=1)	1	0.005	0.472	0.943

Note: # Bonferroni-adjusted p-values. The #P-value was not statistically significant confirming that there is no design effect in our list experiment.

Table A.4. Difference in cheating history by gender across grades

Gender	Newly enrolled students: Mean of response value – Control	Newly enrolled students: Mean of response value – Treatment	Newly enrolled students: Estimated prevalence (1)	Higher-grade students: Mean of response value – Control	Higher-grade students: Mean of response value – Treatment	Higher-grade students: Estimated prevalence (2)	Difference (2) – (1)
Female	1.875	1.775	-0.100	2.141	2.471	0.330**	0.430**
	[1.004]	[0.969]	(0.127)	[0.963]	[1.042]	(0.157)	(0.202)
Male	1.600	1.901	0.301**	1.908	2.333	0.425***	0.125
	[0.953]	[1.165]	(0.113)	[0.912]	[0.972]	(0.146)	(0.185)

*Note: Standard deviations in square brackets. Standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Appendix for Chapter 3

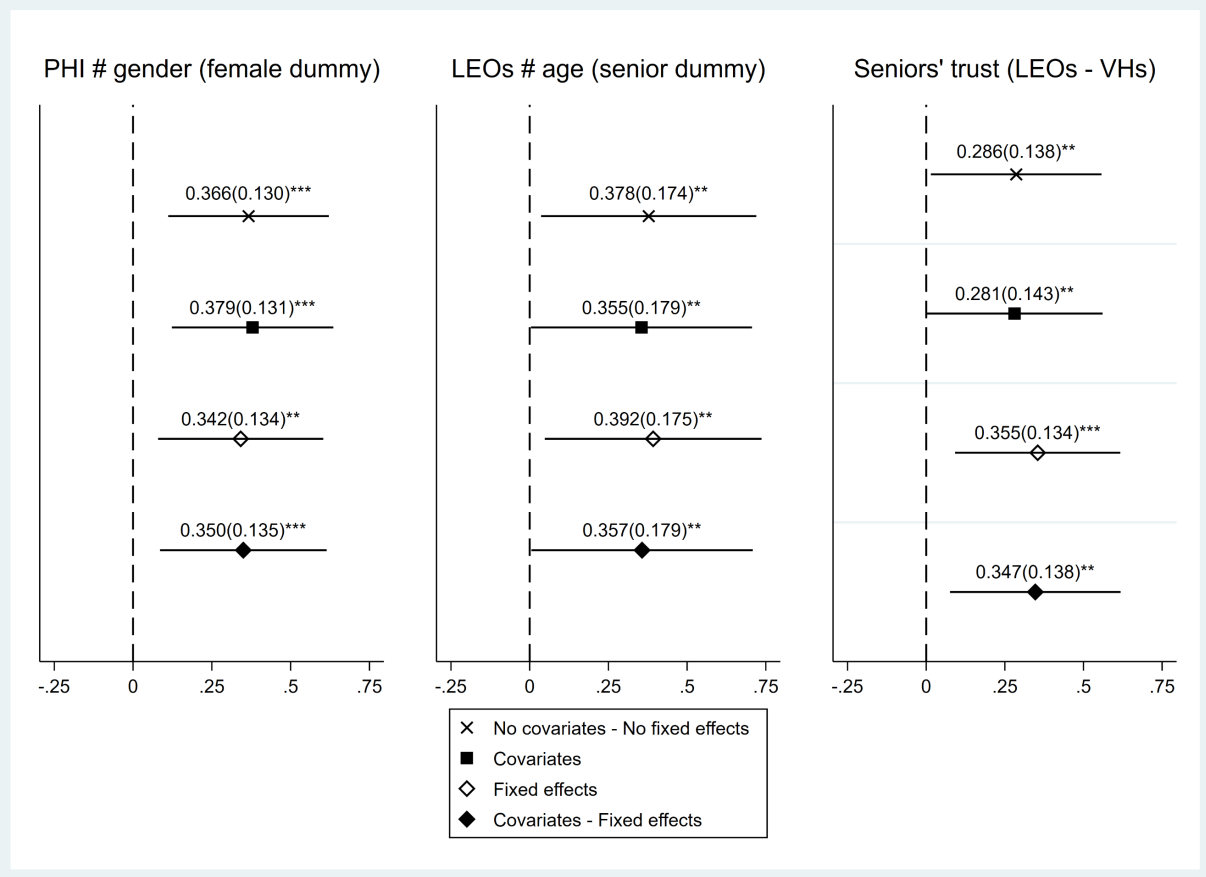

Figure B.1. Sub-group robustness tests at 95% confidence interval.

*Note: Figure B.1a represents robustness tests of heterogeneity in treatment effects by gender (female dummy). Figure B.1b represents robustness tests of heterogeneity in treatment effects by age group. Figure B.1c represents robustness tests of heterogeneity in treatment effects of senior farmers' trust. Covariates include age, gender, ethnicity, education, co-operatives membership, VietGAP group membership, farm size, and tea revenue. Fixed effects at the commune level. Robust standard errors in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.*

Table B.1. The design effect test of Chapter 3

	Proportion	N	Response value (v)						p-value
			0	1	2	3	4	5	
List experiment (C-T1)									
Row 1	Treatment T1	289	0.00	5.54	29.76	34.26	29.76	0.69	
Row 2	$Pr(Y_n \leq v \mid T_n=1)$		0.00	5.54	35.29	69.55	99.31	100.00	
Row 3	Control B	294	0.00	4.42	32.65	59.52	3.40	-	
Row 4	$Pr(Y_n \leq v \mid T_n=0)$		0.00	4.42	37.07	96.60	100.00	-	
Row 5	Row4 - Row2		0.00	-1.12	1.78	27.05	0.69		0.537
List experiment (C-T2)									
Row 1	Treatment T1	293	0.34	3.75	35.15	34.81	25.26	0.68	
Row 2	$Pr(Y_n \leq n \mid T_n=1)$		0.00	4.10	39.25	74.06	99.32	100.00	
Row 3	Control B	294	0.00	4.42	32.65	59.52	3.40	-	
Row 4	$Pr(Y_n \leq v \mid T_n=0)$		0.00	4.42	37.07	96.60	100.00	-	
Row 5	Row4 - Row2		0.00	0.32	-2.18	22.54	0.68		0.707

Appendix for Chapter 4

Table C.1. The design effect test of Chapter 4

	Proportion	N	Response value (v) 0	1	2	3	4	5	p-value
List experiment (C-T1)									
Row 1	Treatment T1	290	0.00	3.79	20.34	50.69	21.72	3.45	
Row 2	$Pr(Y_n \leq v \mid T_n=1)$		0.00	3.79	24.14	74.83	96.55	100.00	
Row 3	Control A	297	0.34	3.37	47.81	45.79	2.69	-	
Row 4	$Pr(Y_n \leq v \mid T_n=0)$		0.34	3.70	51.52	97.31	100.00	-	
Row 5	Row4 - Row2		0.34	-0.09	27.38	22.48	3.45		0.597
List experiment (C-T2)									
Row 1	Treatment T2	289	0.00	3.46	16.26	48.44	29.07	2.77	
Row 2	$Pr(Y_n \leq v \mid T_n=1)$		0.00	3.46	19.72	68.17	97.23	100.00	
Row 3	Control A	297	0.34	3.37	47.81	45.79	2.69	-	
Row 4	$Pr(Y_n \leq v \mid T_n=0)$		0.34	3.70	51.52	97.31	100.00	-	
Row 5	Row4 - Row2		0.34	0.24	31.80	29.14	2.77		0.956

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